

Specialization Enables Diversification: Country Expertise and the Structure of Loan Syndicates^{*}

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Abstract

Bank specialization enables diversification within a single syndicated loan. In lending to U.S. exporters, syndicates led by banks specialized in a borrower's primary export destination attract participants with little relevant expertise, mobilizing capital such lenders would otherwise rarely supply. Their entry is durable: novice participants deepen destination exposure through further lending within the certifying arranger's network. When geoeconomic crises strike those markets, this matching intensifies and spreads rise, but expert leads eliminate the statistically detectable crisis premium. This pattern suggests that certification allows low-exposure participants to bear risk at low marginal cost because the lead's expertise substitutes for their own.

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1 Introduction

Should a bank specialize its loan portfolio or diversify it? A long-standing literature frames these as competing strategies: diversification reduces a bank’s exposure to idiosyncratic local risks and lowers the probability of failure (Winton, 1999; Goetz et al., 2016), while specialization enhances screening and monitoring effectiveness, since expansion into unfamiliar markets weakens banks’ informational advantage (Acharya et al., 2006). Mounting evidence indicates that, in practice, specialization prevails at the portfolio level: banks concentrate their lending in a few industries (Blickle et al., 2026), specialize geographically for small firms and sectorally for large firms (Casado and Martinez-Miera, 2025), and specialize in financing exports to particular destination countries (Paravisini et al., 2023). Common to this body of work is the view that specialization and diversification are portfolio-level alternatives—a bank, in effect, picks one side of the trade-off.

This paper shows that specialization and diversification are not alternatives but complements that coexist *within* a single credit arrangement: we document how destination-country expertise shapes the allocation of lenders across syndicate roles, why expert leads enable participation by lenders who would otherwise be excluded by information frictions, and when this allocation lowers borrowing costs. In a typical syndicated loan, a lead arranger screens and monitors the borrower, while participant lenders contribute funding without necessarily possessing detailed borrower-specific information. Prior syndication work centers on the information the lead produces about the borrower through screening and monitoring, effort that participants cannot observe and that the lead makes credible by retaining a share of the loan (Sufi, 2007; Ivashina, 2009). Country expertise is a different object: a portfolio-level stock of lending experience, predetermined relative to any individual deal, and observable ex ante for every active lender. That conventional division of labor does not by itself determine how a common, observable dimension of expertise should sort across syndicate roles. Participants might benefit from holding the same country knowledge as the lead—lenders unfamiliar with a destination could avoid risks they cannot independently evaluate, and expert leads could prefer equally expert partners who are easier to coordinate and less wary of adverse selection—so that expertise sorts positively across roles. Or participants might instead rely on the lead’s certification while supplying risk-bearing capacity from relatively unexposed portfolios, so that expertise sorts

negatively. We show that the second configuration prevails: banks specialized in the borrower’s main export destination take the lead, and their syndicates systematically attract participants with little or no relevant country expertise. The lead’s specialization is precisely what enables the participants’ diversification: expert leads act as information intermediaries, certifying foreign-market exposure and enabling lenders without such expertise to supply capital to markets they would otherwise avoid. Building on [Paravisini et al. \(2023\)](#), who demonstrate that banks’ country-specific lending experience improves their ability to evaluate foreign-market exposure, we treat country expertise as the relevant dimension of specialized knowledge and ask how it shapes the composition and pricing of loans to U.S. firms with significant export exposure.

We start by setting out a simple framework that formalizes this logic and delivers the three hypotheses we test. Its central element is that a bank’s existing exposure to a destination country plays two opposing roles: it lowers the cost of evaluating a borrower whose fortunes depend on that country, and it raises the cost of bearing more of that country’s risk. This matching logic is the engine of our analysis, and the first hypothesis it yields (**H1**) is that syndicates led by arrangers with high expertise in the borrower’s main export country should attract participants with limited or no expertise in that country—*negative assortative matching* in country expertise between the lead and its participants.

To test this hypothesis, we construct a comprehensive dataset combining syndicated loan data from LPC DealScan with geographic revenue exposure data from FactSet Revere for U.S. publicly listed firms from 2004 to 2019. Following [Paravisini et al. \(2023\)](#), we measure a lender’s country expertise as the debt-weighted export specialization to a given country across all its borrowers in the year prior to the origination of the focal loan. This approach captures the intensity of a bank’s lending relationships with firms exporting to specific countries, accounting for both the number of such relationships and their sizes.

Our empirical strategy exploits variation in country expertise within each firm-lead arranger pair over time, combined with stringent fixed effects that control for unobserved heterogeneity along multiple dimensions. We include firm-lead arranger pair fixed effects to absorb time-invariant relationship-specific characteristics, lead arranger-year fixed effects to control for the bank’s overall lending behavior in each year, and country-industry-year fixed effects to account for time-varying

shocks affecting all firms in the same industry exporting to the same primary destination. Our estimates are therefore not driven by borrower-specific characteristics, the bank’s overall lending strategy, or common shocks to similar exporters.

We first establish the core matching result: lead arrangers attract participants with little or no relevant expertise precisely when their own expertise in the borrower’s main export country is high. This matching holds with firm-lead arranger pair, lead arranger-year, and country-industry-year fixed effects in place. That is, it emerges even within the same lending relationship. The economic magnitude is substantial: loans led by expert arrangers assemble syndicates with 12% to 21% lower average participant expertise compared to those led by non-expert arrangers.¹

This negative relationship is economically significant and robust to controlling for the lead arranger’s industry-specific lending practices, excluding loans to borrowers exporting to NAFTA countries, and using alternative measures of participant expertise such as the share of participants with high country expertise or the share of specialized countries that overlap between the lead and participants. We also find an even stronger effect for borrowing firms that derive more than 10% of their revenue from their main export market, which represents economically meaningful foreign exposure. This suggests that country expertise becomes particularly valuable—and the certification role of expert leads more pronounced—when export market dependence is higher.

A key implication of our first hypothesis is that novice lenders should be the ones drawn into expert-led syndicates. To test this, we move from loan-level outcomes to lender-level decisions, using a loan-issuance participation design built on a direct comparison: among all recently active outside lenders that could have participated in a given loan (excluding the lead and prior relationship lenders), which ones actually do? Because every potential lender faces the same borrower and the same loan terms, we can estimate participation decisions with loan facility fixed effects and lender-year fixed effects, absorbing all borrower-specific and lender-specific conditions—and thereby also ruling out the concern that omitted time-varying firm characteristics drive the loan-level results. We find that novice lenders—those in the bottom quartile of prior exposure to the borrower’s main

¹A permutation benchmark that holds syndicate membership fixed and randomly reassigns the lead role shows that exclusion arithmetic cannot fully explain the loan-level association: the observed coefficient is more negative than the mechanical benchmark. Moreover, the lender-level participation results below are immune to such role-assignment mechanics and provide the primary identification.

export country—are generally less likely to join a syndicate, but this participation disadvantage is essentially eliminated when the lead arranger has high expertise in that country.² The effect persists after adding lead arranger-lender pair fixed effects and remains significant for borrowers with economically meaningful ($>10\%$ revenue) exposure to the destination country. These results isolate differential supply-side participation consistent with certification, rather than borrower-driven selection: an expert lead removes the barrier that otherwise keeps low-exposure (diversifying) capital out, reinforcing the conclusion that lead country specialization enables syndicate diversification. The effect is concentrated primarily among lenders with no prior exposure—those with maximal diversification capacity and the steepest informational barrier—for whom an expert lead turns the net participation propensity positive.

The diversification these participants represent is not transitory. In an event-study design around novice lenders’ first entry into a given export market, novices who enter under an expert lead hold significantly larger positions in that country over the following three years than novices whose first entry occurs under a non-expert lead—roughly triple their pre-entry exposure—with no differential pre-trends. This expansion operates largely through subsequent lending within the certifying arranger’s network rather than through independent entry: expert certification sustains an ongoing intermediation relationship rather than a one-off participation.

After establishing this specialization–diversification matching, we ask when it matters most. The mechanism should be especially valuable when the risk being financed is difficult for non-specialists to evaluate. Export-market shocks provide such a setting. Political and institutional disruptions in a borrower’s destination market can affect revenues and creditworthiness, but they are hard to summarize with standard financial ratios and difficult to hedge through conventional contracts. These shocks therefore increase the value of an expert lead arranger’s certification. Examples are abundant: the sovereign debt crisis in the GIIPS countries; the Russia-Ukraine conflicts in 2014 and 2022; the 2016 Brexit referendum; the 2018 U.S.-China trade war; and the comprehensive tariff policies implemented by the U.S. government in 2025. We use local country-risk episodes from [Hassan](#)

²Throughout the paper, we use “novice” as shorthand for low prior lending exposure to the destination country. The expertise measure captures portfolio specialization rather than information directly, so a novice lender need not be unsophisticated in general; it is a lender for whom the destination market represents a small share of its lending history.

et al. (2019) and Hassan et al. (2024) as a stress test of the mechanism: when destination-country information becomes more valuable, do expert leads attract more diversifying participants, and does this syndicate structure affect loan pricing?

Applying the same logic to this setting gives our second hypothesis (**H2**). Because the value of expert certification derives from country-specific information asymmetries, the matching between expert leads and novice participants should intensify when those asymmetries are most severe—that is, when the borrower’s main export market is in crisis. The data support this prediction: when borrowers’ main export markets experience local political or institutional crises, the negative relationship between lead and participant expertise intensifies, with the crisis-period matching effect roughly 2.4 times its tranquil-period counterpart. The intensification is identified most reliably—including under inference that clusters at the destination-country level—among borrowers with economically meaningful export exposure, precisely where the theory predicts destination-country information matters most.

Turning to pricing, we find that local geoeconomic crises raise loan spreads by roughly 3.4%. This premium is economically sensible: unlike market-based risks that firms can typically hedge through derivatives, these crises create non-diversifiable risks that directly affect borrowers’ ability to maintain export revenues and service debt, making them difficult to manage through conventional hedging instruments.

How much of that premium reaches the borrower is the subject of our third hypothesis (**H3**). A destination-country crisis raises the marginal cost of bearing that country’s risk most sharply for lenders already concentrated in it: additional lending doubles down on an exposure they already hold. Participants with little prior exposure, in contrast, hold portfolios nearly orthogonal to the crisis market, so their capacity to bear the risk is largely intact; what they lack is the information to evaluate it—and that is precisely what the specialized lead supplies. If the lead’s information production makes these low-exposure lenders willing to deploy their spare risk-bearing capacity, then expert-led syndicates should mitigate crisis-driven spread hikes specifically through their composition: low-exposure participants, informed by the lead’s screening, become the marginal suppliers of credit when concentrated lenders pull back. Consistent with this hypothesis, we find in reduced form that expert lead arrangers eliminate the statistically detectable crisis premium, a result that is robust

to inference clustered at the destination-country level. Suggestive mechanism evidence points to composition as the channel: syndicates expected to attract more low-exposure lenders experience sharply attenuated crisis-induced spread hikes, and this attenuation is not explained by syndicate size or generic monitoring intensity. This is consistent with the presence of diversified lenders who can bear the destination-country risk at low marginal cost while relying on the specialized arranger’s evaluation of it. Results using the predicted number of novice participants are also consistent with diversified, low-exposure capital, mobilized under expert certification, lowering financing costs when geoeconomic uncertainty is highest. As an additional check on the mechanism, an event study around the 2016 Brexit referendum, a sharp and largely unanticipated shock to a specific export market, investigates how spreads rose for U.S. firms mainly exporting to the U.K. and how higher lead arranger country expertise attenuated this increase.

Our primary contribution is to the literature on bank specialization and diversification. Since [Winton \(1999\)](#) and [Acharya et al. \(2006\)](#), this literature has framed specialization and diversification as a portfolio-level trade-off between monitoring effectiveness and risk reduction (see also [Goetz et al., 2016](#)). Recent evidence documents pervasive specialization: in industries ([Blickle et al., 2026](#)), geographically for small firms and sectorally for large firms ([Casado and Martinez-Miera, 2025](#)), and in financing exports to particular destinations ([Paravisini et al., 2023](#)). We show that this dichotomy dissolves once one looks inside the credit arrangement: specialization and diversification coexist at different layers of the same syndicated loan, with country expertise actively reallocated across syndicate roles. Lead arrangers specialize; their participants diversify; and the former enables the latter. Rather than specialization crowding out diversification, we document a network-based intermediation mechanism in which a specialized lead certifies foreign-market risk and thereby mobilizes diversifying capital from lenders with little prior exposure to the destination market—a mechanism that becomes most valuable when geoeconomic uncertainty is highest.

Second, we contribute to the literature on information production and incentive alignment in loan syndication. Prior work has emphasized the role of lead arrangers in screening and monitoring borrowers, as well as how the need for incentive alignment between lead arrangers and loan participants shapes syndicate structure ([Dennis and Mullineaux, 2000](#); [Sufi, 2007](#); [Ivashina, 2009](#); [Gao and Jang, 2021](#)). Recent studies such as [Saavedra \(2018\)](#) and [Chu et al. \(2024\)](#) provide more evidence on the

implications of within-syndicate differences in expertise and interests. We introduce country-specific expertise as a new dimension of information asymmetry within syndicates, and show that expertise is not only priced through retention and monitoring effort, but also through systematic sorting of participants by knowledge type. By demonstrating that expert leads enable low-exposure lenders to participate and lower borrowing costs precisely when geoeconomic uncertainty is highest, we show that syndication does more than divide screening from funding: it assigns country-specific information production to a specialized lead and reallocates country-risk bearing toward lenders whose lack of prior exposure gives them the greatest capacity to absorb it—lenders whom the information friction would otherwise keep out of the market.

Third, our paper speaks to the literature on how financial intermediaries manage risks under interconnected businesses. [Giannetti and Saidi \(2019\)](#) show that high-market-share lenders internalize negative spillovers along the supply chain; [Doerr and Schaz \(2021\)](#) show that geographically diversified banks maintain loan supply during crises in borrowers’ countries; and [Aldasoro et al. \(2025\)](#) document that non-banks curtail syndicated lending more than banks during such crises. Closest to us, [Alfaro et al. \(2025\)](#) show that banks specialized in Asian trade finance directly eased financial and informational frictions for tariff-hit U.S. importers, helping them establish new supplier relationships in other Asian countries during the 2018–2019 U.S.-China trade tensions, and [Schiller \(2023\)](#) analyzes financial contagion in international supply-chain networks. Relative to these, our contribution is to show that bank specialization operates not only as a direct lender–borrower channel but also as an *intra-syndicate intermediation mechanism*: a country-specialized lead arranger certifies foreign-market risk to participant lenders who lack relevant expertise, mobilizing capital from lenders who would otherwise be less likely to supply it. Specialization by the lead thus enables diversification by participants in the same loan, a role for specialized banks that complements the bilateral channels documented in prior work.

Finally, two adjacent literatures provide essential foundations for our crisis analysis. Research on the real effects of political and institutional uncertainty ([Baker et al., 2016](#); [Pierce and Schott, 2016](#); [Hassan et al., 2019](#); [Clayton et al., 2026](#)), and in particular the country-risk measures of [Hassan et al. \(2024\)](#), allow our identification of local geoeconomic crises; we add evidence that such risks in export destinations carry tangible borrowing-cost effects that specialized bank relationships mitigate.

Relatedly, the literature on international diversification (e.g., [Gervais, 2018](#); [Caselli et al., 2020](#); [Chod et al., 2019](#); [Esposito, 2022](#); [Grossman et al., 2023](#); [Hyun et al., 2024](#)) documents how firms diversify export destinations and supplier bases to mitigate idiosyncratic shocks; we show that international diversification also operates through firms’ strategic reliance on specialized banking relationships, which reallocate country-specific knowledge within syndicates and sustain credit access when export markets are in crisis.

The rest of the paper is organized as follows. Section 2 describes the data and variable construction. Section 3 presents the framework and derives our three hypotheses. Section 4 establishes the matching between specialized lead arrangers and novice participants, at both the loan level and the lender level. Section 5 examines how this matching responds to export-market uncertainty and shapes loan pricing. Section 6 concludes.

2 Data and Measurements

2.1 Data

DealScan database We obtain syndicated loan data from LSEG’s Loan Pricing Corporation (LPC) DealScan legacy database. DealScan contains detailed information on the origination and maturity dates of each loan facility within a loan package, along with the names of its lending banks, loan amount, terms and conditions, and other loan-specific characteristics. We define lenders at the bank holding company level following prior work (see, for example, [Schwert \(2018\)](#)). We aggregate lenders in DealScan to their parents using the link table provided by [Schwert \(2018\)](#). For smaller lenders not covered in this link table, we use the same aggregation method, accounting for ownership changes due to mergers and divestitures. For example, all Bank of America lenders are aggregated under the Bank of America brand. The outstanding loans by Bank One are aggregated under the JP Morgan Chase brand after the former’s merger with the latter in 2004. We use the DealScan-Compustat link table provided by [Chava and Roberts \(2008\)](#) to link DealScan borrower IDs to GVKEYs in Compustat. This link table covers loan facilities till early 2017. We extend the link table to cover the rest of 2017 till 2019, the end of our sample period.³

³We choose to end our sample at the end of 2019 to first avoid potential confounding influence of the disruptive COVID-19 pandemic. Furthermore, Blackstone acquired Thomson Reuters in 2018Q4, the data provider that owns

We focus our analysis at the loan facility level as loan syndicate composition varies across facilities based on loan type and purpose even within the same loan package. We keep only loan facilities classified as credit lines (revolver loans) or term loans. We delete loan facilities with facility start dates later than the corresponding loan packages’ deal active dates, as these are often renegotiated facilities in the DealScan legacy database. We clean up and define lead arrangers in each loan syndicate following the approach of [Chakraborty et al. \(2018\)](#). For our main analysis, since our key measure is based on lead arranger country expertise, we also exclude loan facilities with multiple lead arrangers.

FactSet Revere database The FactSet Revere database is designed to uncover business relationships and market exposures for companies worldwide. Our primary data source is the FactSet Revere Geographic Revenue Exposure dataset, which provides comprehensive geographic revenue breakdown information for more than 49,000 publicly traded companies. This database captures where companies generate their revenues by country and region, offering detailed insights into firms’ international business exposure and geographic diversification strategies. The dataset includes both historical and current geographic revenue distributions going back as far as 2003,⁴ enabling researchers and analysts to track changes in companies’ international footprints over time. The data is structured to provide standardized geographic classifications that facilitate cross-company and cross-temporal comparisons of international business activities.⁵ This data allows us to identify a firm’s major export market based on their revenue share.⁶ For further details on the FactSet Revere relationships database, see [Ding et al. \(2021\)](#) and [Hyun et al. \(2024\)](#).

DealScan, and renamed it Refinitiv. We note that the data structure became significantly different following the acquisition, and we therefore use the legacy version and end our loan sample in 2019 to avoid any potential inconsistency.

⁴Therefore, we start our sample in 2004 since we need to identify lenders’ country expertise in the prior year.

⁵FactSet analysts systematically collect and maintain information from primary public sources such as SEC 10-K annual filings, company-reported segment data, regulatory filings, investor presentations, and press release, and changes based on corporate actions are monitored on regular basis. FactSet employs sophisticated estimation techniques and validation procedures to ensure data quality and consistency across different reporting standards and disclosure practices.

⁶Geographic revenue exposure can reflect cross-border exports as well as sales generated by foreign subsidiaries or local production. Throughout the paper, we use “main export market” as shorthand for the firm’s main foreign revenue market; the economic mechanism we study operates through foreign-market revenue exposure generally rather than through cross-border shipments specifically.

Compustat database We collect firm-level characteristics and balance sheet information from the Compustat Fundamentals Annual database. The Compustat Fundamentals database provides standardized financial statement data (income statements, balance sheets, and cash flow information) for publicly traded companies worldwide. Compustat North America provides the U.S. and Canadian information on more than 13,000 publicly listed companies, and Compustat Global covers over 39,000 non-U.S. and non-Canadian publicly listed firms.⁷ Following standard practice in corporate finance, we exclude firms in utilities and finance industries.

2.2 Measurements

Bank Country Expertise To measure a lender’s expertise in a country, we follow a similar approach as in Paravisini et al. (2023). Using Peruvian data, they show that firms often seek credit from banks specializing in their export destinations. To capture such bank specialization, we first identify all firm-lender pairs with outstanding loan facilities in a given year, based on facility start and end dates reported by DealScan, and the corresponding facility amounts. Since one firm can have not only multiple loan facilities, but also multiple export destinations in a given year, we end up with a firm-lender-facility-country-year panel. A lender’s specialization in a country for a given year can then be calculated with the equation below:

$$EXP_{b,t}^c = \frac{\sum_{i=1}^I \sum_{l=1}^L L_{ilb} X_{i,t}^c}{\sum_{k=1}^C \sum_{i=1}^I \sum_{l=1}^L L_{ilb} X_{i,t}^k}, \quad (2.1)$$

where $X_{i,t}^c$ is firm i ’s export amount to country c in year t , and L_{ilb} is the loan facility amount of outstanding loan facility l between firm i and lender b in year t .⁸ $EXP_{b,t}^c$ thus provides a debt-weighted export specialization measure of lender b in country c in a given year t . Importantly, as Paravisini et al. (2023) point out, since the measure incorporates the value of exports associated with a lender, it addresses the concerns that a lender specializes in a country due to its lending to many exporters relative to other lenders or it simply lends disproportionately to a few large exporters relative to other lenders. In addition to this continuous measure, we classify a lender as a country

⁷We merge the Compustat Fundamentals database with the FactSet Revere database using common identifiers, namely, Ticker, ISIN, CUSIP, and SEDOL.

⁸Note that a loan facility l is year t -specific. So we dropped the t subscript.

expert if its $EXP_{b,t}^c$ is in the top quartile for the corresponding export destination (country) in the given year. A potential concern is that a lender’s measured expertise partly reflects its outstanding loans to the focal borrower itself, so that “expertise” conflates destination-country experience with the strength of a preexisting bilateral relationship. In Appendix B, we recompute the measure excluding the focal borrower from both the numerator and the denominator of equation (2.1); our composition and participation results are unchanged.

In Appendix A, we validate whether the lender country expertise measure we construct using our data on U.S. publicly listed firms yields results consistent with those reported in Paravisini et al. (2023). Specifically, we confirm that firms are, on average, more likely to borrow from lenders that specialize in their main export destinations. In doing so, we categorize lenders’ level of country expertise based on their EXP_b^c in year-country quartiles following Paravisini et al. (2023), and in the regressions we lag these bank country expertise measures by one year.⁹ As Table A.1 in Appendix A demonstrates, lenders with the highest level of specialization (top country-year quartile, Q4) in the borrower’s main export country are substantially more likely to participate in the loan facility.

Local Crisis Indicator Our local crisis indicator comes from Hassan et al. (2024), who use textual analysis of earnings conference calls to measure country risk at the firm-country-quarter level and aggregate it to the country level. They classify a country-quarter as being in a “crisis” if its Country Risk measure exceeds two standard deviations above its country-specific mean, and further distinguish “local” crises from “global” ones based on whether the Global Risk measure (the mean across countries) crosses the same threshold. Since our analyses are at the annual level, we classify a country-year as being in a local crisis if at least one quarter of the loan origination year or the prior year falls within a local crisis. Examples in our sample include the 2011 Q4 sovereign debt crisis in Italy, the 2016 Brexit referendum in the United Kingdom, the 2015–2016 corruption scandal in Brazil, and the 2011 Fukushima disaster in Japan.

2.3 Summary Statistics

[Insert Table 1 here]

⁹We rank lenders for each country-year into quartiles based on the $EXP_{b,t}^c$ measure in the full FactSet-DealScan matched sample of firm-country-bank-year observations.

Table 1 presents summary statistics for our main sample of 9,733 syndicated loan facilities to U.S. publicly listed firms from 2004 to 2019. Our key variables show substantial variation in country expertise across both lead arrangers and participants. Average participant country expertise (excluding the lead) in the borrower’s main export country is 0.034 with a standard deviation of 0.028. The share of participants with high country expertise averages 24.8%, and the share of specialized countries overlapping between the lead and participants averages 66.3%, both with considerable dispersion. About 24% of facilities have a high-expertise (top-quartile) lead arranger, and lead arranger country expertise has a mean of 0.036 and a standard deviation of 0.032.

Local crises occur in 15.8% of facility observations. The all-in-drawn spread averages 200 basis points, ranging from 40 to 450 bps between the 5th and 95th percentiles.

Loan and firm characteristics are typical of syndicated lending to public U.S. firms: average syndicate size is 9.5 lenders, average facility amount is \$645 million, 44.5% of facilities are secured, and 33.8% include performance pricing. The median borrower has total assets of \$3.3 billion and leverage of 26.8%—primarily large firms with significant international operations.

Figure D.1 in Appendix D shows the geographic distribution of borrowers’ main export destinations. Canada is the most common primary destination (roughly 30% of facilities), consistent with its status as the United States’ largest trading partner, followed by Japan, mainland China, Germany, and the United Kingdom. This geographic diversity provides substantial variation in country-specific risks and in the relevance of banks’ specialized knowledge across destination markets.

3 A Simple Framework

Before turning to the data, we formalize the paper’s central idea in a simple model. Its purpose is to make precise how syndication unbundles the two aspects of bank specialization: a bank’s existing exposure to a destination country is simultaneously an *information asset*—knowledge accumulated from lending to borrowers exposed to that country—and a *diversification liability*—an existing exposure that additional lending further concentrates. The model delivers the three hypotheses we take to the data.¹⁰

¹⁰As a by-product, the model also rationalizes two empirical facts documented below: the lead arranger is specialized but sits inside the expertise distribution rather than at its top; and expert certification matters most for lenders with no prior exposure at all.

Its ingredients are standard: retention as a credibility device follows [Leland and Pyle \(1977\)](#), [Holmström and Tirole \(1997\)](#), and [Sufi \(2007\)](#); the participation friction, an information cost that keeps some lenders out of unfamiliar markets, follows [Merton \(1987\)](#); the risk cost, under which a bank prices a new position against the exposure already on its book, follows [Froot and Stein \(1998\)](#); and the tension between information-driven specialization and the diversification motive echoes [Diamond \(1984\)](#), [Winton \(1999\)](#), and [Van Nieuwerburgh and Veldkamp \(2010\)](#). What the framework adds is to show how a single observable bank characteristic—destination-country exposure—has opposing effects on information production and risk-bearing, thereby generating negative assortative matching across syndicate roles and state-dependent crisis pass-through. We deliberately abstain from mathematical exposition in this section and instead provide an intuitive explanation. Online Appendix OB states the environment in full, including the functional forms, regularity conditions, and detailed derivations, and collects the proofs.

3.1 Environment

A firm seeks one unit of debt financing, and its cash flows load on a destination-country shock with intensity $x > 0$ (the foreign-market revenue share). Destination risk, σ^2 , is the variance of that shock, and its variation is what we later associate with local crises. The firm’s quality is unknown: a fraction π of borrowers are bad types whose funding entails an expected loss, and that loss is larger when destination risk is higher. Screening reveals type, but requires country-specific evaluation capacity.

Each of N banks arrives with an existing exposure $w_j \geq 0$ to the destination country—the counterpart of the lender expertise measure $EXP_{b,t}^c$ in equation (2.1)—and is risk averse, with risk aversion γ . Two costs depend on that exposure, and they move in opposite directions. The *information cost* is what a lender spends to come to understand the borrower’s destination exposure—incurred by the lead, which screens the borrower, and by any participant that must evaluate the risk for itself. The *risk cost* is what a lender must be paid to carry that exposure on its own book, and it

falls on everyone who funds a share. This tension is what the framework is built around:

$$\underbrace{\frac{\partial (\text{information cost})}{\partial w}}_{\substack{\text{information asset:} \\ \text{evaluating the borrower is cheaper for the exposed}}} < 0 \quad \text{versus} \quad \underbrace{\frac{\partial (\text{risk cost})}{\partial w}}_{\substack{\text{diversification liability:} \\ \text{bearing the risk is dearer for the exposed}}} = \gamma x \sigma^2 > 0 \quad ,$$

where the risk cost is measured per unit of loan funded. Experience with borrowers exposed to the country lowers the cost of evaluating a new one, so information is cheaper for a bank that has lent there before—though at a decreasing rate, as the first loans to a destination teach more than later ones.¹¹ But a new loan to that destination compounds a position such a bank already holds, so its risk cost is higher. Note that the diversification liability, $\frac{\partial (\text{risk cost})}{\partial w}$, is *constant* in exposure and proportional to destination risk σ^2 : a crisis scales it up, while leaving the cost of evaluating the borrower where it was. The two roles—a lead and a participant—resolve this tension differently because they face different information costs and hold different shares, allowing the framework to place a specialized lender in one role and a diversified lender in the other within the same loan.

A syndicate consists of a lead, who screens and certifies the borrower, and n participants who each choose whether to fund a share α . For the lead’s screening to be credible it must retain a share $\rho \in (0, 1)$ of the loan, an incentive-compatibility requirement we take as given (Holmström and Tirole, 1997; Sufi, 2007). The shares exhaust the loan, $\rho + n\alpha = 1$. The key friction is on the participation margin: before funding, a participant must be able to evaluate the borrower’s destination-country exposure. Under a *certified* expert lead—one whose own exposure clears a threshold $\bar{w}$, so that its assessment is informative—participants can rely on that evaluation and bear no information cost. This threshold maps directly into our empirical treatment, the top-quartile lead-expertise indicator. Absent certification, a participant must evaluate the exposure itself, at a cost $m(w_j)$ that falls with its own experience and is largest, at a finite M , for a bank with no history in the destination market.

Collecting these pieces, lender j ’s required compensation per unit of loan supplied is summarized

¹¹We formalize this in Online Appendix OB by assuming that both the lead’s screening cost and the participant’s evaluation cost are decreasing and convex in exposure.

by the score

$$s_j(\sigma^2) = \gamma x \sigma^2 w_j + \frac{\phi_j + f_j}{\alpha}, \quad \phi_j = \begin{cases} 0 & \text{certified expert lead,} \\ m(w_j) & \text{otherwise,} \end{cases} \quad (3.1)$$

plus a term for the loan's own variance that is the same for every participant, where $f_j \geq 0$ is a lender-specific fixed cost of participating (capital and mandate constraints, monitoring overhead). The score has a simple reading. The first component is the risk cost of exposure, which *multiplies* w_j by destination risk. The second is the lump-sum cost of participating, information plus fixed, which is incurred once whatever the share and so weighs more per unit lent the smaller that share is. Two features drive everything that follows: certification switches the information cost off, and destination risk scales the exposure term while leaving the information term untouched.

Syndicate formation proceeds in two stages, which keeps the participation margin and the pricing margin distinct: first, the n participant slots are filled by the n lenders with the lowest scores; second, the competitive spread is set to compensate the *marginal* (highest-score selected) participant along with the lead. The spread is therefore an outcome of the selection, not an input to it. Both stages condition on the lead: participants' scores depend on it only through its certification status, while the lead's own problem involves no participant object, so the two can be solved in sequence rather than jointly. Alongside certified and self-evaluating (uncertified) syndicates, we use one further comparison in Propositions 2 and 3: *unscreened funding*, in which the same lenders fund the loan on the same shares but without any screening, and so price the expected loss from bad borrowers on top of their risk-bearing costs. It is the benchmark against which the value of certification is measured.

3.2 Results

The three results follow one another naturally. Proposition 1 asks who is selected into a syndicate; Proposition 2 asks how that selection moves as destination risk rises; Proposition 3 asks what the resulting composition implies for the spread. They deliver our three hypotheses in turn.

Proposition 1 (Specialization–diversification matching). Certification determines which lenders a

syndicate can reach, and the lead role falls to a bank that is specialized, but need not be the most specialized.

- (i) *Participants.* Under a certified expert lead, lenders differ systematically only in the cost of bearing destination risk, which rises with exposure; idiosyncratic participation costs perturb the ranking, but only locally. Selection therefore reaches the low-exposure end of the distribution, including banks with no prior exposure at all. Without certification, a participant must also cover its own evaluation cost, which falls steeply with experience; selection then settles in an *interior* range of exposure—away from banks too unfamiliar with the destination to evaluate it, and away from banks too concentrated in it to want more.¹²
- (ii) *The lead.* The lead weighs a screening cost that falls with experience against a concentration cost that rises with it. Because the screening gain flattens as experience accumulates while the concentration cost does not, the two forces balance at an optimum w_C^* : the lead is specialized enough to certify, clearing the threshold $\bar{w}$, but sits inside the expertise distribution rather than at its top.
- (iii) *Across syndicates.* Combining (i) and (ii), syndicates arranged by certified expert leads exhibit systematically lower average participant exposure than those arranged without certification.

Proposition 1 is our first hypothesis (**H1**). Part (iii) is the composition prediction we take to Table 2: syndicates arranged by certified expert leads have systematically less exposed participants on average. Part (i) is sharper than this syndicate-level average, and we test it directly at the lender level: the low-exposure banks that certification allows a syndicate to draw in are the model counterpart of the *novice* (bottom-quartile prior exposure) lenders in our participation design. The prediction sharpens once more: because the evaluation cost certification removes is largest for a bank with *no* prior exposure at all, certification’s effect on participation should be strongest at the zero-exposure margin, which we confirm in Section 4.3.

Part (ii) has its own counterpart. The certification threshold $\bar{w}$ maps into our top-quartile definition of a high-expertise lead, so certified leads sit in the upper tail of the expertise distribution by

¹²Certified and uncertified selection differ only if evaluation costs fall steeply enough near zero exposure relative to risk-bearing costs; the appendix states the condition more formally.

construction.¹³ Part (ii) further shows that the optimum is bounded *above*. Appendix C documents the corresponding pattern in the data. On average, actual lead arrangers sit at the 58th percentile of the within-syndicate expertise distribution and are the most expert member of their syndicate in only 21% of facilities, slightly more often than the 19% that random role assignment would produce.¹⁴ A bank can be *too* specialized to want the lead role.

Proposition 2 (Crises intensify the matching). Destination risk scales the risk-bearing component of a lender’s required compensation, which is proportional to its exposure, but not the information and participation costs, which are lump-sum. A crisis therefore does not make low-exposure banks better informed; it raises what exposed lenders must be paid while leaving unexposed lenders’ costs where they were.

- (i) *Re-sorting*. A lender’s score is what it must be paid to join, so the n slots go to the n cheapest lenders. As destination risk rises, low-exposure lenders become cheaper relative to high-exposure ones and displace them in that queue. The reordering runs one way only: rising risk can flip a pair toward the lower-exposure lender, never toward the higher-exposure one. *Within each syndicate type*, the average exposure of the selected participants is therefore non-increasing in risk, and strictly decreasing whenever this reordering pulls a lower-exposure lender into the syndicate in place of a more exposed one.
- (ii) *A widening gap*. If low-exposure lenders enter the marginal participant set more readily under certification than without it, the decline in average participant exposure described in part (i) is larger for certified syndicates, so the composition gap between the two types widens with risk.

Proposition 2 is **H2**. It states that a crisis genuinely re-sorts the *selected* participant set, not merely the ordering among lenders who never join, and does so most strongly where certification is what brings low-exposure banks in. Empirically, the widening composition gap corresponds to the negative interaction between lead expertise and the local crisis indicator in Table 8.¹⁵

¹³Certification is a threshold property: once lead exposure exceeds $\bar{w}$, participants bear no evaluation cost. The top-quartile indicator therefore maps more closely to this margin, while the continuous measure captures gradations in expertise that the framework abstracts from. We report both throughout.

¹⁴Note that this does not contradict parts (i) and (iii). The framework predicts a downward shift in participants’ *average* exposure when the lead has high expertise, not that the lead outranks every member of its syndicate.

¹⁵While the framework implies that certified syndicates begin re-sorting at a *lower* level of risk than uncertified

Proposition 3 (Crisis pass-through to spreads). The competitive spread compensates the marginal selected participant and the lead, so crisis pass-through depends on who that participant is.

- (i) *Certified syndicates.* Because certification draws in participants with little or no prior exposure, the marginal participant bears the destination risk at a marginal cost approaching zero—provided the pool of such lenders is deep enough to fill the syndicate. Crisis pass-through is then limited to the lead’s compensation plus a term common to every regime.
- (ii) *The alternatives.* Both alternatives transmit more of the crisis. An unscreened pool prices the expected loss from undetected bad borrowers, which itself rises with destination risk. A self-evaluating syndicate has a marginal participant with strictly positive exposure, whose required compensation rises with risk in proportion to that exposure.¹⁶

Proposition 3 is **H3**: expert-led syndicates attenuate the crisis premium because their marginal supplier of credit bears the destination-country risk at negligible marginal cost, relying on the lead’s information production.¹⁷ The retained share also hands the framework a testable comparative static that none of our main tests target: both conditions in Proposition 3 tighten as ρ rises, so the attenuation an expert lead delivers should shrink with the share of the loan the lead itself retains. Online Appendix OC confirms this pattern using DealScan’s reported lead allocations.

Finally, the framework has a natural dynamic extension: participating raises the entrant’s exposure and familiarity with the destination market, lowering its future evaluation costs. The evidence in Section 4.4 indicates that this deepening operates through the certifying lead’s continued intermediation rather than making the entrant immediately self-sufficient, which would require evaluation costs to be partly relationship-specific—a feature outside the present framework.

ones, part (ii) rests on the further condition that their composition then moves *faster* with risk—the property that makes the gap widen rather than open once and stay put. We take the faster case as the empirically relevant one and let H2 test it. Also, the part (ii) statement is local to the empirically relevant range of risk: at extreme risk, uncertified syndicates substitute toward unexposed lenders too and the gap narrows again. Online Appendix OB treats both points formally.

¹⁶The comparison against self-evaluating syndicates requires the lead’s retained share to be small enough, and the comparison against unscreened funding requires the pooling loss to respond strongly enough to destination risk; the proof states both conditions.

¹⁷The framework speaks to this pass-through comparison rather than to spread levels: certification saves participants’ evaluation costs while adding the lead’s compensation, so the tranquil-period level difference is not signed.

4 The Specialization–Diversification Structure of Loan Syndicates

This section presents our central empirical result: syndicates led by country-specialized arrangers systematically attract participants with little or no relevant expertise. If lead arrangers with greater country expertise are better able to screen and certify borrowers’ export market risks, then their syndicates should attract participants with less country-specific knowledge. This implies a negative relationship between lead arranger country expertise and average participant country expertise. We first document this relationship at the loan level, then move to lender-level evidence—a loan-issuance participation design that holds the borrower and the loan fixed and isolates the supply-side participation decisions of novice lenders.

4.1 Empirical Design

Our baseline empirical specification examines how lead arranger country expertise affects the composition of loan syndicates. Specifically, we estimate:

$$AvgParticipantExp_{l,c,t} = \beta LeadExp_{l,c,t-1} + b'_1 X_l + b'_2 Z_{i,t-1} + \alpha_{i,b} + \mu_{b,t} + \theta_{c,j,t} + \epsilon_{l,t} \quad (4.1)$$

where $AvgParticipantExp_{l,c,t}$ measures the average country expertise of participant lenders (excluding the lead arranger) in loan facility l for borrower i ’s main export country c in year t . Note that each facility l is originated in a single year t (to a borrower i), so t denotes the origination year of facility l ; we retain the explicit time subscript when clarity is required. This expertise measure is based on the loan participants’ outstanding loans in the year prior to the origination year of the focal loan facility. $LeadExp_{l,c,t-1}$ is either the continuous measure of lead arranger country expertise in the borrower’s main export country or an indicator for high lead arranger expertise (top-quartile), based on the lead arranger’s outstanding loans in the year before. X_l and $Z_{i,t-1}$ represent loan-level and firm-level controls, respectively, with conformable coefficient vectors b_1 and b_2 .¹⁸

The key to our identification strategy is the inclusion of three sets of high-dimensional fixed

¹⁸Specifically, loan-level controls include syndicate size (the log of number of syndicate members), facility amount (in log), facility maturity (in log), and indicators for secured loans, performance pricing, loan type, and loan purpose. Firm-level controls include firm size (log total assets), market-to-book ratio, leverage, profitability (ROA), tangibility (PP&E/assets), cash flow volatility, and credit rating fixed effects.

effects. First, $\alpha_{i,b}$ represents firm-lead arranger pair fixed effects, which control for all time-invariant characteristics of the lending relationship between borrower i and lead arranger b . This absorbs cross-sectional differences in relationship-specific knowledge, past lending history, and any bilateral matching between particular firms and banks. By including these fixed effects, we identify our coefficients from variation in lead arranger country expertise within the same firm-bank relationship over time. In our sample, we have over 2,000 unique firm-lead arranger pairs, 41% of which experience a switch in the *HighLeadExp* indicator (from 1 to 0 or from 0 to 1) over the sample period. This suggests that we have meaningful variation in our main variable of interest, even under this stringent specification.

Second, $\mu_{b,t}$ denotes lead arranger-year fixed effects, which absorb all time-varying factors affecting a lead arranger’s general lending behavior in a given year, including the bank’s overall lending capacity, risk appetite, regulatory constraints, and market conditions. This ensures that our results are not driven by changes in the lead arranger’s overall lending strategy or market position.

Third, $\theta_{c,j,t}$ represents country-industry-year fixed effects, where c is the borrower’s main export country and j is the borrower’s industry. These fixed effects control for any time-varying shocks to all firms operating in the same industry and exporting to the same primary destination. For example, they absorb industry-specific demand shocks in the export market, changes in trade policies affecting particular sectors and countries, and macroeconomic conditions in the destination country that differentially affect industries.

The coefficient of interest, β , captures how variation in lead arranger country expertise—holding constant the firm-bank relationship, the lead’s overall lending behavior, and common shocks to similar exporters—affects the average expertise level of participants in the syndicate. Our hypothesis predicts $\beta < 0$: syndicates with more expert leads should attract participants with less country-specific expertise, consistent with specialization by leads enabling diversification by participants. Standard errors are double-clustered at the firm and lead-arranger levels to account for potential correlation in residuals along both borrower and lender dimensions.

4.2 Baseline Results

4.2.1 Average participant country expertise in loan syndicate

Table 2 presents our baseline results examining the relationship between lead arranger country expertise and average participant country expertise in loan syndicates. We report results using both the continuous measure of lead arranger country expertise and a binary indicator for high expertise (top-quartile).

[Insert Table 2 here]

Column (1) includes loan controls, rating fixed effects, loan type and purpose fixed effects, lead arranger-year fixed effects, firm-lead arranger fixed effects, and separate country-year and industry-year fixed effects. The coefficient on lead arranger country expertise is negative and statistically significant at the 1% level, with the coefficient estimate of -0.098. This implies that a one-standard-deviation increase in lead arranger country expertise is associated with approximately 9% lower average participant expertise.¹⁹ Column (2) uses the binary high expertise indicator and finds similar results: syndicates led by high-expertise arrangers have significantly lower average participant expertise, representing roughly a 12% decrease relative to the mean.²⁰ Columns (3) and (4) add firm-level financial controls while maintaining all other fixed effects. The results remain virtually unchanged, suggesting that our findings are not driven by observable borrower characteristics that might correlate with both lead expertise and syndicate composition.

Columns (5) and (6) present our most demanding specification, replacing the separate country-year and industry-year fixed effects with country-industry-year fixed effects ($\theta_{c,j,t}$). These fixed effects absorb all time-varying shocks to firms in the same industry exporting to the same primary market. Even in this highly saturated specification, the negative relationship between lead and participant expertise remains economically and statistically significant. The coefficient on lead arranger country expertise is -0.123, while the coefficient on high lead expertise is -0.007. These magnitudes imply that expert leads assemble syndicates with 12-21% lower average participant expertise.

¹⁹Based on the summary statistics (Table 1), this is obtained by $\frac{\hat{\beta} \times \text{Std. of } LeadExp}{\text{Mean of } AvgParticipantExp} = \frac{-0.098 \times 0.032}{0.034} = 0.092$.

²⁰This is obtained by $\frac{\hat{\beta}}{\text{Mean of } AvgParticipantExp} = \frac{-0.004}{0.034} = -0.118$ using Table 1.

The robustness of our results to this demanding specification is particularly noteworthy. Identification comes purely from variation in lead arranger country expertise within the same firm-bank relationship over time, after absorbing all common shocks to similar exporters and the lead’s overall lending behavior. One concern that remains is time-varying firm-specific shocks correlated with both arranger expertise and syndicate composition; we address it in Section 4.3 through a loan-issuance–lender-level design with loan-facility fixed effects, which holds borrower conditions constant and isolates how arranger expertise shapes new lenders’ participation decisions.

[Insert Figure 1 here]

Figure 1 visualizes this central result. We residualize both average participant expertise and lead arranger expertise on the full set of controls and fixed effects from column (5) of Table 2, sort the residualized lead-expertise values into twenty equal-sized bins, and plot bin means, adding back sample means for readability. The negative gradient is visible across the entire distribution of lead expertise rather than being driven by a handful of extreme syndicates, and the fitted line’s slope equals the regression coefficient in column (5) by construction.

One may worry that part of this loan-level association is mechanical: because the lead is excluded from the participant average, holding syndicate membership fixed, assigning a higher-expertise member to the lead role automatically lowers the measured expertise of the remaining participants. Appendix C quantifies this channel with a permutation benchmark that holds each syndicate’s membership fixed, reassigns the lead role at random, and re-estimates equation (4.1) with all fixed effects re-encoded to the placebo lead. Random reassignment does generate a negative placebo slope on average, so exclusion arithmetic explains a meaningful portion of the loan-level association; the observed coefficient is roughly twice the mechanical benchmark, though the randomization p -value (0.18) indicates the two are not sharply separated statistically. The sharpest version of the concern—designating the most expert member as lead—produces a strongly *positive* placebo slope rather than a negative one. More importantly, the lender-level participation design in Section 4.3 is immune to this arithmetic by construction, because it compares participation decisions across candidate lenders facing the same facility rather than measuring the composition of the residual syndicate. We therefore treat the loan-level magnitudes as descriptive of the equilibrium matching

and rest the identification of differential participation on the lender-level evidence.

4.2.2 Alternative Measures of Participant Expertise

To ensure that our results are robust to different measures of participant expertise, we examine two alternative dependent variables. First, we consider the share of loan participants (excluding the lead arranger) with high country expertise (top-quartile) in the borrower’s main export market. Second, we examine the share of participant-specialized countries (top-quartile expertise) that overlap with the countries in which the lead arranger specializes.

[Insert Table 3 here]

Table 3 reports results using two different dependent variables. Columns (1) and (2) use the share of loan participants with high country expertise in the borrower’s main export market. Columns (3) and (4) use the share of specialized countries that overlap between the lead and participants.

Both measures show consistent patterns. Columns (2) and (4), respectively, imply that having a high-expertise (top-quartile) lead arranger lowers the share of participants with high country expertise by around 35% and the share of specialized countries that overlap between the lead and participants by around 5%, relative to the respective sample means. These results confirm that expert leads attract syndicates consisting of lenders with less relevant geographic knowledge, regardless of how we measure participant expertise.

4.2.3 Export Exposure Relevance

Another concern is that our measure of a firm’s primary export market may capture economically marginal foreign sales when overall foreign exposure is small, so that the baseline results could be driven by cases without meaningful export dependence. To address this, we re-estimate all loan-level specifications after imposing a 10% threshold on the borrower’s revenue share from its primary export country.²¹ The threshold is not arbitrary: under U.S. GAAP segment reporting rules, firms must disclose geographic revenue separately for any country whose share of consolidated revenues is

²¹The mean and median of the main export market revenue share is around 10% (Mean: 12.8%, Median: 8.57%). Therefore, we consider 10% as a threshold indicating meaningful foreign exposure.

material, and 10% is the materiality benchmark commonly applied in practice.²² This ensures that the identified “main export market” corresponds to a material foreign exposure substantial enough to plausibly shape lenders’ information needs and perceived risks.

[Insert Table 4 here]

Table 4 presents the results. The results remain qualitatively unchanged and, if anything, become stronger. Across all three dependent variables—average participant country expertise, share of participants with high expertise, and share of specialized countries that overlap between the lead and participants—we consistently find significant negative coefficients on lead expertise measures. For average participant expertise, the coefficient on lead arranger country expertise is -0.146 compared to -0.123 in Table 2, while the coefficient on high lead expertise is -0.009 compared to -0.007 in Table 2.

These amplified effects are consistent with the interpretation that country expertise matters most when foreign-market revenues are economically significant—precisely when monitoring needs, informational asymmetries, and exposure to foreign shocks are greatest. This strengthens our baseline interpretation: the specialization-diversification pattern reflects economically meaningful foreign dependence rather than classification noise or incidental export activity.

4.2.4 Additional Robustness to Alternative Specifications

We conduct several robustness tests to address potential confounding factors. First, one might worry that our country expertise measure simply captures industry expertise, as banks that lend to firms exporting to particular countries might specialize in the industries of those exporters. To address this point, we replace lead arranger-year fixed effects with lead arranger-industry-year fixed effects (defined using borrowers’ 2-digit SIC codes), which control for the lead’s lending practices in a particular industry in a given year.

Appendix Table D.11 presents these results. Even after absorbing all variation in lead arranger lending behavior at the industry-year level, we continue to find that higher lead arranger country expertise is associated with significantly lower average participant expertise. The coefficient estimates

²²Under SFAS 131 / ASC 280, 10% is the explicit threshold for both reportable operating segments (a segment is reportable if it accounts for at least 10% of combined revenues) and individual-customer disclosure (a single customer must be disclosed if it accounts for at least 10% of consolidated revenue). Firms commonly extend the same 10% benchmark to country-level geographic disclosures as well.

are similar to or slightly larger than our baseline estimates, indicating that country expertise represents a distinct dimension from industry expertise.

Second, we examine whether our results are driven by loans to firms exporting primarily to NAFTA countries (Canada and Mexico), which account for a substantial share of U.S. exports. Trade with NAFTA partners might be perceived as less risky or more familiar to U.S. lenders, potentially reducing the value of specialized country expertise.

Appendix Table D.12 reports results excluding loans to borrowers whose main export destination is Canada or Mexico. The negative relationship between lead and participant expertise persists with similar or larger magnitudes, suggesting our findings are not specific to geographically or culturally proximate markets.

Third, within a firm-lead arranger pair, measured expertise could change over time because the borrower’s main export destination switches (say, from Canada to China) rather than because the lead’s knowledge of a given market changes. We therefore re-estimate the baseline on the subsample of borrowers whose main export destination never changes over our sample period, so that all identifying variation comes from the evolution of lender expertise for a fixed destination. The results strengthen considerably: the coefficient on continuous lead expertise is -0.218 ($t = -5.46$) and on the high-expertise indicator -0.019 ($t = -6.17$), roughly twice the full-sample magnitudes (Appendix Table D.4; 2,960 facilities). Destination switching, if anything, attenuates the baseline estimates.

4.3 Lender-Level Evidence: Participation Propensity of Novice Lenders

We now move from loan-level composition outcomes to lender-level participation decisions, sharpening identification by holding the borrower and loan terms fixed. While the loan-level evidence documents that syndicates led by expert arrangers include participants with lower country expertise, the interpretation may still be confounded by unobserved borrower fundamentals. Firms experiencing time-varying improvements in credit quality, export opportunities, or risk management capacity might simultaneously attract a lead arranger with stronger export-country expertise and a set of less-expert participant lenders. Although our baseline specification incorporates an extensive set of fixed effects, residual concerns may remain because lender participation decisions can still co-move with borrower-level shocks.

To sharpen identification, we turn to a loan-issuance design that compares potential lenders who could have participated in a given loan to those who actually do. For each loan facility, we construct the set of all active lenders in the previous year—i.e., lenders that were active participants in the syndicated loan market. These lenders form the relevant supply-side choice set. We then ask whether each potential lender actually joins the facility. This approach allows us to include loan-facility fixed effects, absorbing all borrower characteristics, loan terms, lead-arranger attributes, and any loan-specific credit demand. Variation comes solely from cross-lender differences in country expertise.

We further restrict attention to non-relationship lenders—excluding the lead arranger and any lender that previously lent to the firm—to isolate the decision of new participants responding to the lead arranger’s expertise rather than to past bilateral relationships. Using this panel, we estimate new participation as a function of lender expertise and its interaction with the lead arranger’s expertise:

$$Participation_{l,k} = \beta_1 Novice_{k,c,t-1} + \beta_2 (Novice_{k,c,t-1} \times HighLeadExp_{l,c,t-1}) + \alpha_l + \mu_{k,t} + \epsilon_{l,k} \quad (4.2)$$

where k indexes a potential outside (participant) lender, distinct from the lead arranger b , and $Participation_{l,k}$ is an indicator for lender k participating in facility l . $Novice_{k,c,t-1}$ indicates that the lender has low expertise in the borrower’s main export country c , and $HighLeadExp_{l,c,t-1}$ indicates the lead arranger has high expertise in that country. Because the facility index l determines the origination year t , the subscript $t - 1$ denotes the year before facility l is originated. Both expertise measures carry the $t - 1$ subscript because they are computed from each lender’s outstanding loans in that year—the year prior to the focal loan’s origination—ensuring that they are predetermined relative to the participation decision. We define low country expertise as the lender’s relevant expertise measure being in the bottom quartile of the country-year prior to origination year of the focal loan facility. We include loan facility fixed effects (α_l), which control for all loan-specific and borrower-specific factors affecting participation decisions, and lender-year fixed effects ($\mu_{k,t}$), which absorb time-varying lender characteristics.

[Insert Table 5 here]

Table 5 presents the results. Column (1) shows that novice lenders are generally less likely to participate in loan facilities. However, column (2) shows that novice lenders are more likely to participate if the facility is led by an expert arranger. The interaction term $Novice \times HighLeadExp$ is positive and statistically significant at the 5% level, indicating that expert leads specifically attract novice participants.

Column (3) adds lead arranger-participant lender pair fixed effects, which control for time-invariant relationship characteristics between specific lead-lender pairs (e.g., repeated syndication partnerships, correspondent banking relationships, or geographic proximity). The interaction effect remains positive and significant, confirming that expert leads enable participation by novice lenders beyond general lead-lender relationship effects.

Columns (4)-(6) repeat this analysis for the subsample of borrowers with more than 10% revenue share from their main export market. Again, we find that novice lenders are less likely to participate overall (column 4), but this effect is significantly mitigated when the lead arranger has high country expertise (columns 5 and 6).

The theory’s sharpest prediction concerns the *zero-exposure margin*: banks with no prior exposure to the destination country have the greatest spare risk-bearing capacity and face the steepest informational barrier, so certification should matter most for them.

[Insert Table 6 here]

Table 6 tests this prediction directly by splitting novice lenders into those with strictly zero prior exposure and those with positive-but-bottom-quartile exposure. The certification effect is concentrated primarily at the zero-exposure margin: for zero-exposure lenders the interaction with high lead expertise is 0.003 ($t = 2.99$) in the full candidate pool—large enough to turn their net participation propensity under an expert lead *positive*—while positive-exposure novices show no differential response (interaction 0.000). Column (2) shows the same pattern, with a larger interaction (0.004, $t = 2.87$), when the candidate pool is restricted to lenders that participated, in the prior year, in at least one facility of the same loan-type group (credit line versus term loan) and the same one-digit borrower industry—a more realistic feasible-lender set. Column (3) shows that the result is equally robust to reclassifying expert leads with the leave-one-borrower-out expertise measure of

Appendix B (interaction 0.003, $t = 2.77$), so it does not reflect the lead’s preexisting relationship with the focal borrower. Column (4) adds lead arranger-lender pair fixed effects, addressing the concern that certain leads repeatedly invite the same banks and those banks happen to have zero destination exposure: the zero-exposure interaction remains significant at the 5% level (0.002, $t = 2.58$; 0.003, $t = 2.06$, in the untabulated restricted-pool specification), while the positive-exposure interaction is small and at most marginally significant, so the zero-exposure margin remains the dominant channel within lead-lender relationships as well. Appendix Table D.9 reports the corresponding pooled restricted-choice-set specification.

These results provide support for our view that expert lead arrangers serve a certification role, enabling novice lenders to join syndicates by reducing information asymmetries about export-related credit risks. Novice lenders who lack the information to assess country-specific export risks are willing to participate when an expert lead certifies loan quality, which enables geographic diversification that would otherwise be infeasible. In addition to providing support for the key mechanism, the results in this test also help address any residual concern that the baseline findings reflect borrower-driven selection or omitted firm-level shocks. Because all lenders in the choice set face the same borrower and loan terms, the loan-issuance design isolates differential supply-side participation consistent with the certification mechanism.

One may wonder whether our participation-based evidence reflects reverse causality, namely, that loan facilities attracting a greater share of novice participants require an expert lead arranger, rather than expert leads recruiting low-exposure lenders. The loan-issuance-lender design limits this concern: by conditioning on the full set of alternative potential lenders and absorbing facility fixed effects, it compares lenders facing the same facility, so the result that novice lenders are differentially more willing to join only when the lead arranger has high expertise in the borrower’s main export market is unlikely to be driven by facility-level demand for an expert lead. While the design does not pin down which side first initiates the pairing, our objective is not to disentangle this, but to document the equilibrium mechanism that consistently links lead specialization with participant diversification. Whether driven by novice lenders’ demand for expert certification or by expert arrangers’ ability to mobilize diversified capital, both interpretations reinforce the same economic insight: expertise at the top enables diversification at the margin. This matching pattern, rather

than its direction, is the mechanism through which syndicates reallocate international risk.

4.4 Post-Participation Evidence: Do Novice Lenders Diversify?

The participation results establish that expert leads draw novice lenders into loans exposed to unfamiliar export markets. Participation alone, however, does not establish that the syndicate delivers *durable* diversification: a novice lender might join a single expert-led facility and never lend toward that market again. If expert certification genuinely seeds new country exposure, novice lenders who first enter a market under an expert lead should build more expertise in that market subsequently than novice lenders whose first entry occurs under a non-expert lead.

We test this prediction with an event-study design. We construct a lender-country-year panel of the expertise measure EXP_b^c and identify, for each lender-country pair, the first facility participation by a novice (bottom-quartile expertise) lender in a loan whose borrower’s main export country is c . This yields 956 events, of which 274 occur under a high-expertise (top-quartile) lead arranger. We then trace each entrant’s expertise in country c from three years before to three years after the event, with the year preceding origination as the baseline period. Our specification includes event fixed effects, which absorb all time-invariant differences across entrants (including the level of the lead’s expertise), and country-calendar-year fixed effects, which absorb aggregate expertise trends in each destination market; standard errors are clustered at the lender level. Because the focal loan itself enters the expertise measure while outstanding for treated and control entrants alike, this common mechanical component is differenced out: the estimates capture whether expert-led entry is followed by *additional* lending toward country c .

[Insert Figure 2 here]

Figure 2 plots the expert-led versus non-expert-led differential in EXP_b^c around the event; Appendix Table D.3 reports the underlying estimates. Pre-event differentials are individually and jointly insignificant (joint p -value 0.28). After entry, the differential turns positive at every horizon and is statistically significant one and three years out: by the third year, novices who entered under an expert lead hold 0.016 more expertise in the destination country than novices who entered under a non-expert lead—roughly triple the pre-entry expertise of these entrants, or about half a standard

deviation of the lender expertise distribution. The differential operates on the intensive margin: an indicator for any positive expertise shows no differential response (Appendix Table D.3, columns 3-4), consistent with expert-led entry deepening subsequent exposure rather than merely flipping lenders from zero to positive.

These dynamics complete the diversification half of our mechanism: expert leads do not simply fill out syndicates with one-off diversifying capital, as the low-exposure lenders they attract go on to hold materially larger positions in precisely the market the expert certified. We are careful, however, about the channel. When we count entrants’ *subsequent* participations in the same destination market while excluding the entry borrower and all facilities arranged by the entry lead, expert-led entrants in fact expand *less* outside the original arranger’s network than non-expert-led entrants (Appendix Table D.5; the difference at the any-participation margin is zero). The post-entry expansion therefore operates within the certifying lead’s orbit—repeat interactions with the same arranger and borrower network—indicating that the persistent exposure works through continued intermediation rather than autonomous market entry, and possibly through a degree of relational dependence on the certifying arranger. We read the evidence as durable portfolio expansion sustained by an ongoing intermediation relationship, rather than as a one-time transfer of knowledge that makes the entrant self-sufficient; on either reading, the diversification enabled by certification persists well beyond the original loan.

4.5 The Matching Holds Outside Crisis Periods

A central element of our argument is that the specialization–diversification matching is a structural feature of loan syndicates rather than a phenomenon that arises only in turbulent periods. To establish this, we re-estimate our baseline composition specifications and the loan-issuance participation design on the subsample of loan facilities originated when the borrower’s main export market is *not* in a local crisis—approximately 84% of the sample.

[Insert Table 7 here]

Table 7 presents the results. Panel A reports the loan-level composition specifications with the full set of fixed effects from Tables 2 and 3. The matching remains clearly visible in tranquil

periods. For the share of high-expertise participants (columns 3 and 4), the no-crisis coefficients are essentially indistinguishable from the full-sample estimates: -1.061 for the continuous lead-expertise measure and -0.087 for the top-quartile indicator, compared with -1.044 and -0.087 in Table 3. For average participant expertise, the top-quartile indicator remains negative and significant at the 1% level (column 2), while the continuous measure retains its negative sign but attenuates to about half its full-sample magnitude and loses statistical significance (column 1), suggesting that crisis periods contribute part of the variation captured by the continuous measure. The two measures capture complementary aspects of the same mechanism: the indicator tracks the certification margin of Section 3, while the continuous measure also reflects gradations in lead expertise on either side of the cutoff. That the indicator remains stable in tranquil periods while the continuous measure attenuates is consistent with certification operating at a threshold rather than smoothly in expertise.

Panel B repeats the loan-issuance participation design of Table 5 in tranquil periods. Novice lenders remain generally less likely to join syndicates, but are differentially more willing to participate when the lead arranger is an expert in the borrower’s main export country: the interaction coefficients are statistically significant and essentially identical to the full-sample estimates in Table 5.

Taken together, these results support the view that the matching mechanism operates in normal times: expert leads assemble syndicates of less-specialized participants, and novice lenders sort into expert-led syndicates, even absent any crisis. The crises examined next amplify a structure that is already in place—and reveal its value.

5 When Does the Structure Matter Most? Crises, Syndicate Composition, and Loan Pricing

Having established the specialization–diversification matching within syndicates, we now ask when it matters most. We focus on local political and institutional crises in borrowers’ main export markets. Because these crises arrive as discrete, country-specific shocks—external to any individual borrower–lender relationship, and with timing and severity that are difficult for domestic lenders to anticipate—they let us move beyond the cross-sectional matching pattern and observe how expert leads shape syndicate composition and pricing around sharp changes in country risk. This section

presents two sets of results. First, we show that the matching between expert leads and novice participants intensifies when the borrower’s main export market is in crisis (our second hypothesis). Second, we show that crises carry a loan-pricing premium and that expert leads eliminate the statistically detectable portion of it; the composition evidence is consistent with the mobilization of low-exposure participants being the channel (our third hypothesis).

5.1 Syndicate Composition during Export Market Crises

If expert lead arrangers act as information intermediaries by certifying loan quality to participants who lack destination-specific knowledge, this certification role should become more valuable during periods of heightened information asymmetry. We test this by examining how the relationship between lead and participant expertise varies with political and institutional crises in the borrower’s main export market.

We measure such crises with the local crisis indicator from [Hassan et al. \(2024\)](#), which captures discrete episodes of sharply elevated political or institutional uncertainty.²³ These crises represent unhedgeable shocks to institutional stability that directly disrupt trade flows and payment confidence, such as the 2011 sovereign debt crisis in Italy, the 2016 Brexit referendum, and the 2016 corruption scandal in Brazil.

We augment our baseline specification with an interaction between lead arranger expertise and the crisis indicator as follows.

$$\begin{aligned} AvgParticipantExp_{l,c,t} = & \beta_1 HighLeadExp_{l,c,t-1} + \beta_2 (HighLeadExp_{l,c,t-1} \times LocalCrisis_{c,t}) \\ & + \beta_3 LocalCrisis_{c,t} + b'_1 X_l + b'_2 Z_{i,t-1} + \alpha_{i,b} + \mu_{b,t} + \theta_{c,j,t} + \epsilon_{l,t} \end{aligned} \quad (5.1)$$

where $LocalCrisis_{c,t}$ is the local crisis indicator for the borrower’s main export country. We estimate this specification with both the continuous lead-expertise measure and the top-quartile indicator (as

²³Because crisis-driven country risk tends to persist beyond a crisis’s onset—and loans originated in the year following a crisis still embed elevated risk—we classify a country as being in a local crisis if the local crisis indicator from [Hassan et al. \(2024\)](#) equals one in either year t or year $t - 1$ (or both). Because the underlying measure is constructed from firms’ own earnings-call discussions, it reflects risks that are salient to exposed firms; our identifying assumption is therefore not that crises are unforeseeable, but that their onset and severity are external to any individual U.S. borrower–lender relationship.

written).

[Insert Table 8 here]

Table 8 presents the results. The interaction between lead expertise and the local crisis indicator is negative and significant for both measures of lead expertise. For the continuous measure (column 1), the tranquil-period slope of -0.105 nearly doubles during crises (an additional -0.096, significant at the 1% level). For the top-quartile indicator (column 2), the total effect of high lead expertise during crises is -0.017 (-0.007 - 0.010), representing roughly a 50% reduction in average participant expertise relative to the mean—about 2.4 times the non-crisis effect of high lead expertise (-0.007, or roughly 21%).

The intensification is concentrated precisely where export exposure is economically meaningful. Among borrowers deriving more than 10% of revenue from the main export market (the materiality subsample of Table 4), the crisis interaction is -0.027—nearly three times the full-sample interaction—so that the total crisis-period effect of an expert lead (-0.034) is roughly as large as the sample mean of participant expertise itself (Appendix Table D.7).

These results suggest that information frictions intensify during crises, making the certification role of expert leads more valuable: when country-specific information is most critical and asymmetries are most severe—and for the borrowers whose foreign exposure makes that information most relevant—expert leads enable greater diversification by low-exposure lenders who rely on their screening.²⁴

We now turn to these pricing implications. If expert leads provide certification that enables diversified, low-exposure lenders to participate—lenders whose capacity to bear the destination-country risk is greatest precisely because that risk is a small part of their portfolios—their presence should mitigate the increase in borrowing costs that would otherwise arise during crises.

²⁴Because the crisis indicator varies at the destination-country-year level, we also assess inference that respects country-level dependence. The full-sample composition interaction retains its sign but is estimated less precisely under a wild-cluster bootstrap by destination country ($p = 0.27$ for column 2). The material-exposure interaction in Appendix Table D.7, however, is robust to the same exercise (wild-cluster bootstrap $p = 0.03$): the crisis-period intensification of the matching is identified most reliably where export exposure is economically meaningful, consistent with the theory. The pricing results in Section 5.3.3 are likewise robust to country-level inference.

5.2 Direct Effect of Local Crises on Loan Spreads

We start by investigating whether local geoeconomic crises increase loan costs. Specifically, we estimate

$$Ln(Spread)_{l,t} = \beta LocalCrisis_{c,t} + b'_1 X_l + b'_2 Z_{i,t-1} + \alpha_{i,b} + \mu_{b,t} + \theta_{j,t} + \epsilon_{l,t} \quad (5.2)$$

where $Ln(Spread)_{l,t}$ is the natural logarithm of the all-in-drawn spread (in basis points) for facility l at origination and $LocalCrisis_{c,t}$ is the local crisis indicator for the borrower's main export market. We include the same loan and firm controls as before, along with firm-lead arranger pair fixed effects, lead arranger-year fixed effects, and industry-year fixed effects.

Column (1) of Table 9 presents the result. Local political or institutional crises significantly increase loan spreads: the coefficient on *Local crisis* is 0.034, implying that crises raise spreads by approximately 3.4% on average. This represents a meaningful increase in borrowing costs: the average loan has a 200-basis-point spread, and the crisis premium amounts to about 7 basis points on average. This premium reflects elevated and difficult-to-mitigate credit risk: unlike market-based risks that firms can hedge through derivatives, these institutional shocks directly threaten borrowers' export revenues and debt-service capacity.

5.3 Mitigating Role of Expert Lead Arrangers

We next examine whether expert lead arrangers mitigate crisis-induced spread hikes. We augment equation (5.2) with the high lead arranger expertise dummy and its interaction with the local crisis dummy as follows:

$$\begin{aligned} Ln(Spread)_{l,t} = & \beta_1 LocalCrisis_{c,t} + \beta_2 HighLeadExpl_{l,c,t-1} \\ & + \beta_3 (HighLeadExpl_{l,c,t-1} \times LocalCrisis_{c,t}) \\ & + b'_1 X_l + b'_2 Z_{i,t-1} + \alpha_{i,b} + \mu_{b,t} + \theta_{j,t} + \epsilon_{l,t} \end{aligned} \quad (5.3)$$

5.3.1 Predicted Novice Participation

More importantly, we are not simply interested in the direct effect of high lead arranger expertise on loan pricing. The key conjecture of our paper is that expert lead arrangers' ability to assemble syndicates with diversifying capital from novice lenders, who would otherwise be unwilling to participate, reduces loan spreads during geoeconomic crises. To investigate the effect of this mechanism on loan pricing, we employ a two-stage approach to measure the propensity of novice lenders to participate in each loan facility. In the first stage, we estimate outside lenders' participation decisions as a function of their expertise level and the lead arranger's expertise. Specifically, we estimate a version of equation (4.2) from Section 4, augmented with lead arranger-lender pair fixed effects:²⁵

$$Participation_{l,k} = \beta_1 Novice_{k,c,t-1} + \beta_2 (Novice_{k,c,t-1} \times HighLeadExp_{l,c,t-1}) + \alpha_l + \mu_{k,t} + \nu_{k,Lead(l)} + \epsilon_{l,k} \quad (5.4)$$

where $Novice_{k,c,t-1}$ indicates outside lender k has low or zero expertise in country c (bottom-quartile), $HighLeadExp_{l,c,t-1}$ indicates the lead arranger has high expertise (top-quartile), and we include loan facility fixed effects (α_l), lender-year fixed effects ($\mu_{k,t}$), and lead arranger-lender pair fixed effects ($\nu_{k,Lead(l)}$). The pair fixed effects control for repeated syndication partnerships between specific lenders and leads.

From this regression, we obtain fitted probabilities $\hat{p}_{l,k}$ for each outside lender k to participate in facility l . We then construct two facility-level measures:

$$\widehat{Particip}_l = \frac{1}{|\mathcal{B}_l^{Novice}|} \sum_{k \in \mathcal{B}_l^{Novice}} \hat{p}_{l,k} \quad (5.5)$$

$$Num\widehat{Novice}_l = \sum_k \hat{p}_{l,k} \times Novice_{k,c,t-1} \quad (5.6)$$

where $\mathcal{B}_l^{Novice}$ is the set of all outside lenders with low expertise in the borrower's main export country (i.e., $Novice_{k,c,t-1} = 1$). $\widehat{Particip}_l$ represents the average predicted probability that novice lenders

²⁵Note that column (3) in Table 5 incorporates these fixed effects.

participate in facility l , while $\widehat{NumNovice}_l$ represents the predicted number of novice participants.

5.3.2 Novice Participation and Loan Pricing

In the second stage, we examine whether loans with higher predicted novice participation experience lower spreads during crises:

$$\begin{aligned} Ln(Spread)_{l,t} = & \beta_1 LocalCrisis_{c,t} + \beta_2(\widehat{P}_l \times LocalCrisis_{c,t}) \\ & + \beta_3\widehat{P}_l + b'_1X_l + b'_2Z_{i,t-1} \\ & + \alpha_{i,b} + \mu_{b,t} + \theta_{j,t} + \epsilon_{l,t} \end{aligned} \quad (5.7)$$

where $\widehat{P}_l$ is either $\widehat{Particip}_l$ or $\widehat{NumNovice}_l$.

5.3.3 Results on Loan Pricing Tests

Table 9 presents the results. Column (1) estimates equation (5.2), the direct effect of local crises discussed above, and column (2) shows the main effects. The coefficient on *LocalCrisis* increases from that in column (1), confirming that crises raise spreads when borrowers are matched with non-expert leads.²⁶ Notably, we find a significant negative coefficient for the interaction term, *HighLeadExp* $\times$ *LocalCrisis*, with the coefficient estimate of -0.149. This large negative coefficient indicates that expert leads substantially offset crisis-induced spread hikes. The point estimate of the net crisis effect for borrowers matched with expert leads is negative ($0.049 - 0.149 = -0.100$), and a formal test cannot reject that it equals zero ($p = 0.15$): an expert arranger eliminates the statistically detectable crisis premium.²⁷ This offset is consistent with the role of expert arrangers in certifying borrowers and mobilizing diversified outside capital precisely when uncertainty is highest and less hedgeable.

²⁶The coefficient on *HighLeadExp* is also positive, suggesting that expert leads may charge a monitoring premium in non-crisis periods.

²⁷Appendix Table D.8 reports the full set of inference exercises. The interaction is robust to how inference accounts for the country-level variation in the crisis indicator: clustering by destination country ($t = -2.20$), three-way clustering by firm, lead arranger, and country ($t = -2.18$), and a wild-cluster bootstrap by country ($p < 0.01$, with the crisis level effect at $p = 0.02$) all preserve the result. Leave-one-country-out estimates over the ten largest destination markets all remain negative, ranging from -0.248 to -0.121 . Excluding mainland China—which supplies roughly 70% of crisis-period facilities (Appendix Table D.10)—yields -0.121 ($t = -1.49$), and excluding the United Kingdom yields -0.122 ($t = -1.58$); the loss of precision in these two cases reflects the removal of most identifying variation rather than a change in the estimate, and all eight remaining exclusions are significant at the 5% level, with the Canada and Japan exclusions strengthening the effect.

[Insert Table 9 here]

The natural next question is why expert lead arrangers are able to mitigate the elevated financing costs associated with geoeconomic crises. To investigate whether this effect indeed manifests through the mechanism we identify, in which expert leads attract lenders with little or no country-specific expertise, we use the loan-level measure of predicted novice participation, based on each novice lender’s fitted participation probability in the facility using equations (5.4) and (5.5), and interact it with the crisis indicator. Column (3) of Table 9 presents the result of this analysis. We find that, indeed, the interaction term between the average predicted participation probability of novice lenders and local crisis has a significant and negative coefficient. Note that we include the predicted variable in percentage points. It has a distribution with a modest level of variation, with a mean of 0.445 and an interquartile range of 0.102. Therefore, although coefficients appear large in magnitude, an interquartile increase in this predicted novice participation during a local crisis reduces loan spreads by roughly 10 percent ($-0.989 \times 0.102 = -0.101$). Because interaction models are most interpretable at economically meaningful reference points, we also re-estimate the specification with the participation measure centered at its mean: the marginal crisis effect is +0.040 ($p < 0.01$) at the 25th percentile of predicted low-exposure participation, statistically zero at the median, and -0.047 ($p = 0.10$) at the 75th percentile—the crisis premium is borne by loans whose syndicates draw least on diversified capital.

Two caveats qualify how much weight this two-stage evidence can bear. First, the first-stage participation regression includes loan-facility fixed effects estimated from realized participation, so the fitted probabilities partly embed facility-level attractiveness rather than representing a purely ex ante prediction; the usual generated-regressor caveats also apply. Second, a fully predetermined alternative—the share of the lead’s syndication partners over the prior three years with low expertise in the borrower’s destination country—does not reproduce the interaction (Appendix Table D.6), suggesting that the composition channel is not identified off the lead’s historical network alone. We therefore present the participant-composition results as suggestive mechanism evidence consistent with Proposition 3, while resting the paper’s pricing claim on the reduced-form result that expert leads offset the crisis premium.

Column (4) combines the effect of high lead arranger expertise and predicted novice participation, to assess their joint explanatory power. Once predicted novice participation and its interaction with local crisis are included, the interaction term between high lead arranger expertise and local crisis no longer has a significant coefficient. We caution that this attenuation is not a formal mediation test—both regressors are equilibrium outcomes—but the pattern is consistent with participant composition, rather than the lead’s own balance-sheet strength or monitoring intensity, being the channel through which expert leads mitigate crisis-period financing costs.

Column (5) introduces country-industry-year fixed effects to further address concerns that the local crisis indicator may capture broader country-level macroeconomic shocks coinciding with local political or institutional crises in borrowers’ main export markets. These fixed effects absorb all time-varying shocks at the level of the borrower’s main export country $\times$ its industry $\times$ the loan year, including changes in foreign demand conditions, regulatory shifts, or sector-specific trends, thus purging the crisis variable of any country-level economic confounders that might jointly affect borrower risks and lender behavior.²⁸

5.4 Number of Novice Participants

In Table 10, we examine an alternative measure to corroborate our findings: the predicted number of novice participants ($\widehat{NumNovice}_l$) rather than their average participation probability. Column (1) shows that the predicted number of novice participants significantly reduces crisis spreads, captured by the significantly negative coefficient on $\widehat{NumNovice} \times LocalCrisis$.

[Insert Table 10 here]

Column (2) adds the predicted number of all new participants ($\widehat{NumAll}_l$) as a control. If our mechanism is purely about syndicate size rather than participant expertise, both variables

²⁸We do not include country-industry-year fixed effects in columns (1) to (4) because they fully absorb the standalone local crisis indicator, preventing us from directly estimating the average effect of local crises on loan spreads. In column (5), however, our focus is on the interaction between local crisis and the predicted novice participation measure. Importantly, the coefficient of this interaction remains negative and statistically significant, and its magnitude increases. This amplification is expected: once country-industry-year fixed effects strip away all common country-industry shocks, the remaining identifying variation isolates how syndication structure differentially moderates the effect of crises within otherwise comparable borrower-export market cells. The stronger coefficient therefore reflects a cleaner estimate of the mechanism, i.e. expert-led assembling of diversified low-exposure capital, after netting out confounding macroeconomic forces.

should have similar effects. Instead, we find that only novice participants reduce crisis spreads: the coefficient on $\widehat{NumNovice} \times LocalCrisis$ remains negative and significant, while the coefficient on $\widehat{NumAll} \times LocalCrisis$ is small and insignificant. This pattern is consistent with participant composition—specifically, the inclusion of lenders without relevant expertise—rather than syndicate expansion alone, contributing to the cost reduction.

Column (3) further controls for high lead expertise. The coefficient on $\widehat{NumNovice} \times LocalCrisis$ remains negative, while the effect of $HighLeadExp \times LocalCrisis$ becomes insignificant as in column (4) of Table 9. Column (4) additionally includes country-industry-year fixed effects and finds the strongest evidence: the coefficient on $\widehat{NumNovice} \times LocalCrisis$ is significant and large in magnitude (-1.514), while the corresponding coefficient for all new participants is only weakly positive (0.378) in this most saturated specification.

5.5 Discussion on Mechanism Tests

These results support a division of labor within the syndicate between information production and risk-bearing. A destination-market crisis raises the marginal cost of bearing that market’s risk most sharply for lenders whose portfolios are already concentrated in it: additional lending compounds an exposure they already hold, and they rationally demand a larger premium to supply it. Participants with little prior exposure hold portfolios nearly orthogonal to the crisis market; for them, the marginal cost of bearing the risk is low. What these lenders lack is not balance-sheet capacity but information—and that is what the specialized lead supplies. Under the lead’s screening and certification, low-exposure participants can price the risk from a position of genuine diversification rather than staying out of the market altogether.

This mechanism reconciles our findings on syndicate composition and loan pricing. Expert leads assemble syndicates with lower average participant expertise not as a byproduct of their specialization but because their certification converts diversified lenders’ risk-bearing capacity into usable credit supply. The participants they attract provide funding on relatively favorable terms during crises not because they misprice the risk, but because they genuinely bear it at lower marginal cost than concentrated lenders—while relying on the lead’s information production to overcome the barrier that would otherwise keep them out.

By the same logic, participant lenders with substantial existing exposure to the crisis country face compounding concentration costs and demand higher compensation—which is why syndicates tilted toward experienced participants do not deliver the same pricing relief, as the predicted-number-of-participants results in Table 10 indicate.

This highlights an important function of loan syndication in international credit markets: it separates information production, which is concentrated in the specialized lead, from risk-bearing, which is allocated to diversified participants. The separation is most valuable during geoeconomic shocks, when country-specific information is most critical and the gap between concentrated and diversified lenders’ costs of bearing the risk is widest.

Event Study: The 2016 Brexit Referendum. As an additional check on the mechanism, Online Appendix OA presents an event study around the 2016 Brexit referendum—a salient, well-defined geoeconomic shock to a specific export market. Among U.S. borrowers whose primary export destination is the U.K., loan spreads rose sharply following the referendum relative to borrowers exporting to non-crisis markets, and higher lead arranger country expertise significantly attenuated this increase. The direction and significance of these effects mirror our main crisis-pricing results, reinforcing the mechanism in a single, sharp setting. Given the concentrated comparison group (Canada alone accounts for 68% of the event-study sample), we treat the episode as corroborating evidence.

6 Conclusion

This paper shows that bank specialization and diversification—long treated as competing portfolio-level strategies—coexist within a single credit arrangement. In syndicated lending to U.S. exporters, banks specialized in the borrower’s main export destination take the lead arranger role, and their syndicates systematically attract participants with little or no relevant country expertise who join by relying on the lead’s certification of foreign-market risk. The diversification this enables persists: novice lenders who first enter a market under an expert lead maintain and deepen their exposure over the following years through subsequent lending within the certifying arranger’s network. This matching is a structural feature of syndicates, but it matters most under stress. It intensifies during local political or institutional crises in borrowers’ main export markets, when information

asymmetries are most severe. Crises raise loan spreads, yet expert leads eliminate the statistically detectable crisis premium, and suggestive composition evidence is consistent with the low-exposure participants they attract driving this reduction in borrowing costs. More broadly, our findings show that bank specialization can support diversification by participants in the same loan, not only by the specialist's own borrower. A country-specialized lead certifies foreign-market risk to participant lenders who lack relevant expertise, reallocating international expertise across syndicate roles and mobilizing funding from lenders who would otherwise be less likely to participate—precisely when geoeconomic uncertainty is highest.

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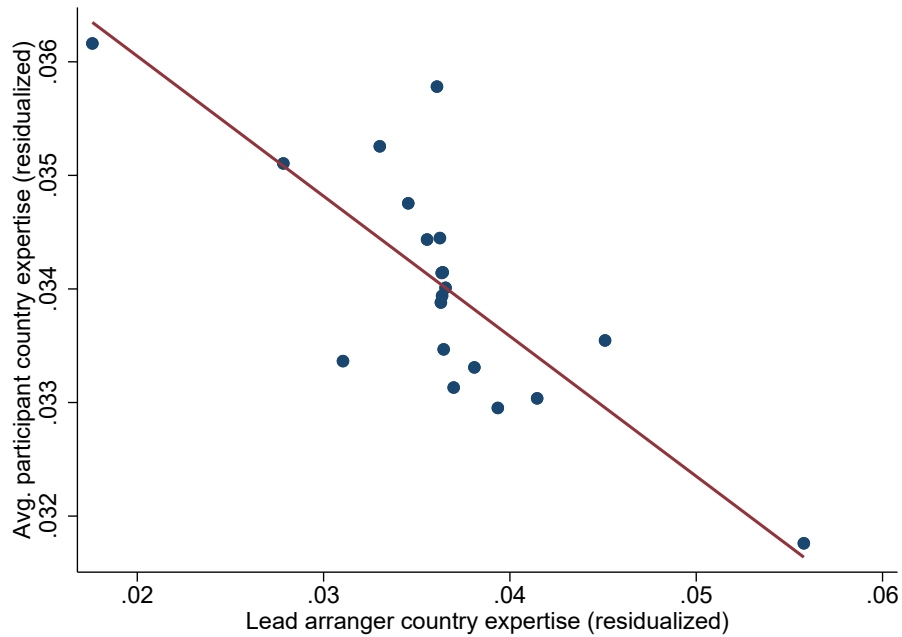
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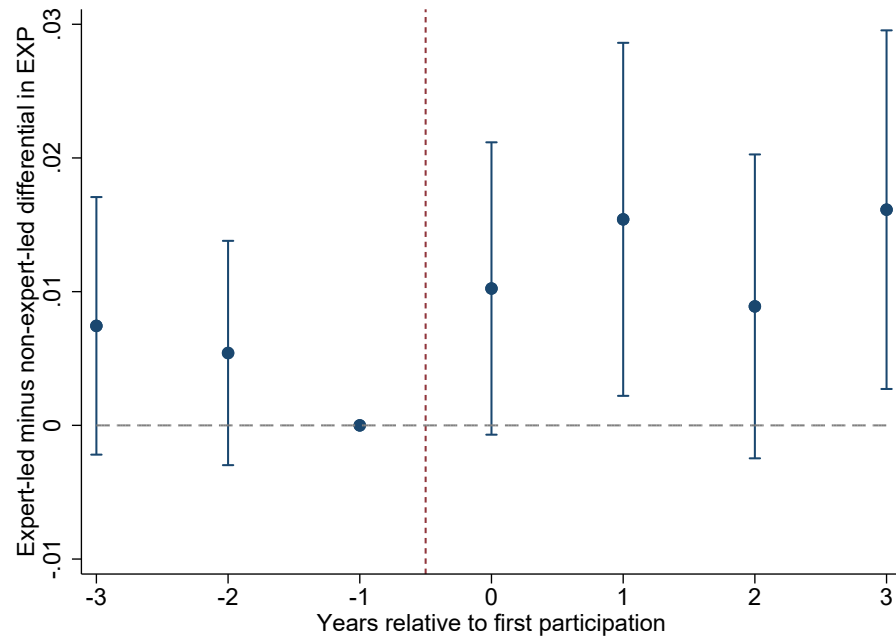
Figures and Tables

Figure 1: Specialization at the Top, Diversification at the Margin



Notes. This figure presents a binned scatter plot of average participant country expertise against lead arranger country expertise in the borrower's main export country. Both variables are residualized on the full set of loan and firm controls and fixed effects from column (5) of Table 2 (rating, loan type, and loan purpose fixed effects; lead arranger-year fixed effects; country-industry-year fixed effects; and firm-lead arranger pair fixed effects), with sample means added back for readability. Residualized lead expertise is sorted into twenty equal-sized bins; each dot plots the within-bin means. The fitted line's slope equals the coefficient estimate in column (5) of Table 2 (-0.123). The sample covers syndicated loan facilities to U.S. publicly listed firms from 2004 to 2019.

Figure 2: Novice Entrants' Expertise around First Participation: Expert-Led vs. Non-Expert-Led



Notes. This figure plots event-study estimates of the differential in country expertise EXP_b^c between novice lenders whose first participation in a loan exposed to export market c occurs under a high-expertise (top-quartile) lead arranger and novice lenders whose first such participation occurs under a non-expert lead. Events are the first facility participation by a bottom-quartile-expertise lender in a loan whose borrower's main export country is c (956 events, 274 expert-led). The horizontal axis measures expertise years relative to the origination year; the baseline period is the year preceding origination. The specification includes event fixed effects and country-calendar-year fixed effects; standard errors are clustered at the lender level. Vertical bars are 95% confidence intervals. The underlying estimates are reported in Appendix Table D.3.

Table 1: Summary Statistics

Variable	N	Mean	Std.Dev.	5th	25th	Median	75th	95th
Key variables:								
Average loan participant country expertise	9,733	0.034	0.028	0.003	0.015	0.027	0.046	0.085
Sh. of participants with high country expertise	9,733	0.248	0.243	0	0	0.214	0.370	0.667
Sh. of specialized countries overlapped with lead	9,733	0.663	0.340	0	0.432	0.800	0.963	1
High lead arranger country expertise	9,733	0.236	0.425	0	0	0	0	1
Lead arranger country expertise	9,733	0.036	0.032	0.004	0.014	0.026	0.048	0.100
Local crisis	9,733	0.158	0.364	0	0	0	0	1
Loan spread (bps)	8,193	200.35	122.92	40	125	175	250	450
Loan facility level variables:								
Number of lenders	9,733	9.485	7.183	2	4	8	12	25
Facility amount (\$ millions)	9,733	645.26	902.18	12	100	300	770	2,500
Maturity (months)	9,733	54.04	17.64	12	48	60	60	84
Secured	9,733	0.445	0.497	0	0	0	1	1
Performance pricing	9,733	0.338	0.473	0	0	0	1	1
Firm level variables:								
Total assets (\$ millions)	9,733	15,557.66	35,071.12	285.02	1,107.10	3,321.08	12,038.15	78,625
Market-to-book	9,733	1.457	0.908	0.538	0.850	1.204	1.785	3.263
Leverage	9,733	0.290	0.182	0.005	0.165	0.268	0.397	0.622
Profitability	9,733	0.136	0.069	0.044	0.092	0.126	0.168	0.265
Tangibility	9,733	0.248	0.198	0.033	0.099	0.187	0.342	0.677
Cash flow volatility	9,733	0.009	0.010	0.001	0.003	0.005	0.010	0.029

Notes. This table presents summary statistics for the main variables used in the analysis. The sample consists of 9,733 syndicated loan facilities-by-year-level observations that are linked to U.S. publicly listed firms (borrowers) and their balance sheet and geographic revenue exposure information from 2004 to 2019. The dataset is constructed by merging DealScan, FactSet Revere, and Compustat Fundamental Annual datasets. Average loan participant country expertise measures the debt-weighted export specialization of participant lenders (excluding the lead arranger) in the borrower’s main export country. High lead arranger country expertise is an indicator for top-quartile expertise in the borrower’s main export market. Local crisis is an indicator from [Hassan et al. \(2024\)](#) for periods when the borrower’s main export destination experiences heightened political or institutional uncertainty. Loan spread is measured in basis points. Firm-level variables are from Compustat. All continuous variables are winsorized at the 1st and 99th percentiles.

Table 2: Lead Arranger and Participant Country Expertise

	Average loan participant country expertise					
	(1)	(2)	(3)	(4)	(5)	(6)
Lead arranger country expertise	-0.098*** (-2.815)		-0.098*** (-2.812)		-0.123*** (-2.869)	
High lead arranger country expertise		-0.004*** (-3.138)		-0.004*** (-3.265)		-0.007*** (-4.856)
N	9,493	9,493	9,493	9,493	8,721	8,721
Loan Controls	✓	✓	✓	✓	✓	✓
Firm Controls			✓	✓	✓	✓
Rating FE	✓	✓	✓	✓	✓	✓
Loan Type FE	✓	✓	✓	✓	✓	✓
Loan Purpose FE	✓	✓	✓	✓	✓	✓
Lead Arranger-Year FE	✓	✓	✓	✓	✓	✓
Firm-Lead Arranger FE	✓	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓		
Industry-Year FE	✓	✓	✓	✓		
Country-Industry-Year FE					✓	✓
Adjusted R-squared	0.744	0.743	0.744	0.743	0.773	0.772

Notes. This table examines the relationship between lead arranger country expertise and average participant country expertise in loan syndicates. The dependent variable is the average country expertise of participant lenders (excluding the lead arranger) in the borrower's main export country. Lead arranger country expertise is the debt-weighted export specialization measure EXP_b^c in columns (1), (3), and (5), and an indicator for high expertise (top-quartile) in columns (2), (4), and (6). Loan controls include syndicate size, facility size (in log), facility maturity, and indicators for secured loans and performance pricing. Firm controls include firm size (log assets), market-to-book, leverage, ROA, tangibility, and cash flow volatility. All specifications include rating fixed effects, loan type and purpose fixed effects, lead arranger-year fixed effects, and firm-lead arranger pair fixed effects. Columns (1)-(4) include separate country-year and industry-year fixed effects; columns (5)-(6) include country-industry-year fixed effects. Standard errors are clustered at the firm and lead-arranger levels. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Alternative Measures of Participant Country Expertise

	Sh. of participant with high country expertise		Sh. of specialized countries overlapped with lead	
	(1)	(2)	(3)	(4)
Lead arranger country expertise	-1.044*** (-3.679)		-0.666** (-2.160)	
High lead arranger country expertise		-0.087*** (-6.572)		-0.033* (-1.810)
N	8,721	8,721	8,721	8,721
Loan controls	✓	✓	✓	✓
Firm controls	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓
Loan Type FE	✓	✓	✓	✓
Loan Purpose FE	✓	✓	✓	✓
Country-Industry-Year FE	✓	✓	✓	✓
Lead Arranger-Year FE	✓	✓	✓	✓
Firm-Lead Arranger FE	✓	✓	✓	✓
Adjusted R-squared	0.697	0.698	0.800	0.799

Notes. This table examines the relationship between lead arranger country expertise and alternative measures of participant expertise. In columns (1)-(2), the dependent variable is the share of loan participants (excluding the lead) with high country expertise (top-quartile) in the borrower's main export market. In columns (3)-(4), the dependent variable is the share of specialized countries that overlap between the lead and participants. All specifications include loan and firm controls, rating fixed effects, loan type and purpose fixed effects, country-industry-year fixed effects, lead arranger-year fixed effects, and firm-lead arranger pair fixed effects. Standard errors are clustered at the firm and lead arranger levels. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 4: The Importance of Export Exposure Intensity

	Main export market revenue share > 10%					
	Average participant country expertise		Sh. of participant with high country expertise		Sh. of specialized countries overlapped with lead	
	(1)	(2)	(3)	(4)	(5)	(6)
Lead arranger country expertise	-0.146*** (-3.983)		-2.094*** (-5.063)		-1.634*** (-6.832)	
High lead arranger country expertise		-0.009** (-2.328)		-0.176*** (-5.031)		-0.072** (-2.586)
N	3,481	3,481	3,481	3,481	3,481	3,481
Controls	✓	✓	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓	✓	✓
Loan Type FE	✓	✓	✓	✓	✓	✓
Loan Purpose FE	✓	✓	✓	✓	✓	✓
Country-Industry-Year FE	✓	✓	✓	✓	✓	✓
Lead Arranger-Year FE	✓	✓	✓	✓	✓	✓
Firm-Lead Arranger FE	✓	✓	✓	✓	✓	✓
Adjusted R-squared	0.761	0.761	0.714	0.715	0.807	0.807

Notes. This table examines the relationship between lead arranger country expertise and syndicate composition for borrowers with substantial export exposure. The sample is restricted to loans where the borrower derives more than 10% of revenue from its main export market (above the median exposure). Columns (1)-(2) use average participant country expertise as the dependent variable. Columns (3)-(4) use the share of participants with high country expertise (top-quartile). Columns (5)-(6) use the share of specialized countries that overlap between the lead and participants. All specifications include loan and firm controls, rating fixed effects, loan type and purpose fixed effects, country-industry-year fixed effects, lead arranger-year fixed effects, and firm-lead arranger pair fixed effects. Standard errors are clustered at the firm and lead arranger levels. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Probability of Novice Lender Participation

	D(Participation)					
	Full sample			Main exp. mkt. rev. share>10%		
	(1)	(2)	(3)	(4)	(5)	(6)
Novice lender	-0.001*** (-3.379)	-0.002*** (-4.026)	-0.001*** (-3.178)	-0.003*** (-4.538)	-0.003*** (-5.124)	-0.003*** (-4.042)
Novice lender×High lead arranger country expertise		0.002** (2.030)	0.002** (2.423)		0.003** (2.148)	0.002** (2.151)
N	2,449,416	2,449,416	2,431,622	1,100,260	1,100,260	1,087,153
Loan Facility FE	✓	✓	✓	✓	✓	✓
Lender-Year FE	✓	✓	✓	✓	✓	✓
Lead arranger-Lender Pair FE			✓			✓
Adjusted R-squared	0.074	0.074	0.091	0.069	0.069	0.097

Notes. This table examines whether novice lenders (those with low or zero country expertise) are more likely to participate in loans led by expert arrangers. The sample includes all loan facilities matched with all active lenders in the market who are not existing lenders of the borrower. Active lenders are those participating in any new loan origination in the year prior to facility start. Novice lender is an indicator for lenders whose country expertise in the borrower's main export market falls in the bottom quartile. The dependent variable equals one if the lender participates in the facility and zero otherwise. Columns (1)-(3) use the full sample; columns (4)-(6) restrict to borrowers with more than 10% revenue share from their main export market. All specifications include loan facility fixed effects and lender-year fixed effects. Columns (3) and (6) additionally include lead arranger-lender pair fixed effects. Standard errors are clustered at the firm and lender levels. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Certification at the Zero-Exposure Margin

	D(Participation)			
	Full choice set (1)	Restricted choice set (2)	Leave-one-out lead (3)	Full choice set (4)
Zero-exposure lender	-0.001** (-1.989)	-0.002 (-1.235)	-0.001* (-1.743)	-0.001 (-1.331)
Zero-exposure lender×High lead arranger country expertise	0.003*** (2.994)	0.004*** (2.870)	0.003*** (2.766)	0.002** (2.578)
Low-positive-exposure lender	-0.002*** (-3.204)	-0.003*** (-2.992)	-0.002*** (-3.277)	-0.001*** (-2.949)
Low-positive-exposure lender×High lead expertise	0.000 (0.129)	0.000 (0.039)	0.000 (0.195)	0.001* (1.724)
N	2,449,416	1,111,776	2,449,416	2,431,622
Loan Facility FE	✓	✓	✓	✓
Lender-Year FE	✓	✓	✓	✓
Lead arranger-Lender Pair FE				✓
Adjusted R-squared	0.074	0.091	0.074	0.091

Notes. This table splits novice lenders in the loan-issuance participation design of Table 5 into lenders with strictly zero prior exposure to the borrower’s main export country and lenders with positive but bottom-quartile exposure. The dependent variable equals one if the candidate lender participates in the facility. Column (1) uses the full candidate pool of active non-relationship lenders; column (2) restricts candidates to lenders that participated, in the year before the facility start, in at least one facility of the same loan-type group (credit line versus term loan) and the same one-digit borrower industry; column (3) uses the full pool but classifies expert leads with the leave-one-borrower-out expertise measure of Appendix B; column (4) uses the full candidate pool and adds lead arranger-lender pair fixed effects. All specifications include loan facility fixed effects and lender-year fixed effects; standard errors are clustered at the firm and lender levels. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 7: The Matching Holds Outside Crisis Periods

Panel A: Syndicate composition (loan level)				
	Average participant country expertise		Sh. of participants with high country expertise	
	(1)	(2)	(3)	(4)
Lead arranger country expertise	-0.065 (-1.148)		-1.061*** (-3.501)	
High lead arranger country expertise		-0.004*** (-3.662)		-0.087*** (-7.626)
N	7,236	7,236	7,236	7,236
Loan and Firm Controls	✓	✓	✓	✓
Rating, Loan Type, Loan Purpose FE	✓	✓	✓	✓
Country-Industry-Year FE	✓	✓	✓	✓
Lead Arranger-Year FE	✓	✓	✓	✓
Firm-Lead Arranger FE	✓	✓	✓	✓
Adjusted R-squared	0.787	0.787	0.690	0.692
Panel B: Novice lender participation (lender level)				
	D(Participation)			
	(1)	(2)		
Novice lender	-0.002*** (-4.259)	-0.002*** (-3.504)		
Novice lender×High lead arranger country expertise	0.002* (1.921)	0.002** (2.571)		
N	2,079,031	2,061,231		
Loan Facility FE	✓	✓		
Lender-Year FE	✓	✓		
Lead arranger-Lender Pair FE		✓		
Adjusted R-squared	0.074	0.092		

Notes. This table re-estimates the main composition and participation specifications on the subsample of loan facilities originated when the borrower's main export market is not in a local crisis, as defined by [Hassan et al. \(2024\)](#). Panel A reports loan-level regressions following the most stringent specifications of Tables 2 and 3: the dependent variable is the average country expertise of participant lenders (columns 1-2) or the share of participants with high (top-quartile) country expertise (columns 3-4) in the borrower's main export country. All Panel A specifications include loan and firm controls, rating fixed effects, loan type and purpose fixed effects, country-industry-year fixed effects, lead arranger-year fixed effects, and firm-lead arranger pair fixed effects; standard errors are clustered at the firm and lead arranger levels. Panel B reports the loan-issuance participation design of Table 5 on the same no-crisis subsample: the sample matches each facility with all active outside (non-relationship) lenders, and the dependent variable equals one if the lender participates in the facility. Novice lender is an indicator for lenders whose country expertise in the borrower's main export market falls in the bottom quartile. Both Panel B specifications include loan facility fixed effects and lender-year fixed effects; column (2) adds lead arranger-lender pair fixed effects; standard errors are clustered at the firm and lender levels. A small number of facilities (24) whose main-export-country-year crisis status cannot be assigned are excluded. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Syndicate Composition during Export Market Crises

	Average loan participant country expertise	
	(1)	(2)
Lead arranger country expertise	-0.105** (-2.505)	
Lead arranger country expertise $\times$ Local crisis	-0.096*** (-3.640)	
High lead arranger country expertise		-0.007*** (-4.717)
High lead arranger country expertise $\times$ Local crisis		-0.010** (-2.389)
N	8,697	8,697
Controls	✓	✓
Rating FE	✓	✓
Loan Type FE	✓	✓
Loan Purpose FE	✓	✓
Country-Industry-Year FE	✓	✓
Lead Arranger-Year FE	✓	✓
Firm-Lead Arranger FE	✓	✓
Adjusted R-squared	0.772	0.771

Notes. This table examines how the relationship between lead arranger and participant country expertise varies with political and institutional crises in the borrower's main export market. The dependent variable is the average country expertise of participant lenders in the borrower's main export country. Lead arranger expertise is the continuous debt-weighted specialization measure in column (1) and the top-quartile indicator in column (2). Local crisis is an indicator from [Hassan et al. \(2024\)](#) for periods when the export destination experiences heightened political, policy, or institutional uncertainty based on textual analysis of earnings calls; its standalone term is absorbed by the country-industry-year fixed effects. All specifications include loan and firm controls, rating fixed effects, loan type and purpose fixed effects, country-industry-year fixed effects, lead arranger-year fixed effects, and firm-lead arranger pair fixed effects. The sample is marginally smaller than in Table 2 because the crisis indicator cannot be assigned for a small number of facilities. Standard errors are clustered at the firm and lead arranger levels. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Loan Financing Costs During Local Crisis Period

	Ln(Loan spread)				
	(1)	(2)	(3)	(4)	(5)
Local crisis	0.034*** (2.978)	0.049*** (2.975)	0.429*** (6.173)	0.367*** (3.622)	
High lead arranger country expertise×Local crisis		-0.149** (-2.232)		-0.078 (-0.895)	0.045 (0.485)
High lead arranger country expertise		0.039*** (2.898)		0.036* (1.978)	0.006 (0.0825)
Average predicted participation probability of novice lenders×Local crisis			-0.989*** (-5.340)	-0.813*** (-2.810)	-1.994** (-2.075)
Average predicted participation probability of novice lenders			0.216** (2.516)	0.037 (0.264)	0.178 (0.179)
N	7,982	7,982	7,982	7,982	7,267
Controls	✓	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓	✓
Loan Type FE	✓	✓	✓	✓	✓
Loan Purpose FE	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	
Country-Industry-Year FE					✓
Lead Arranger-Year FE	✓	✓	✓	✓	✓
Firm-Lead Arranger FE	✓	✓	✓	✓	✓
Adjusted R-squared	0.871	0.871	0.871	0.871	0.891

Notes. This table examines whether expert lead arrangers mitigate the effect of local crises on loan spreads. The dependent variable is the natural logarithm of the all-in-drawn spread at loan origination. Local crisis is an indicator from [Hassan et al. \(2024\)](#). High lead arranger country expertise is an indicator for top quartile expertise in the borrower's main export market. Column (1) estimates equation (5.2), the direct effect of local crises on loan spreads. Column (2) estimates equation (5.3) and column (3) estimates equation (5.7), where the average predicted participation probability of novice lenders is constructed from equations (5.4) and (5.5). Column (4) include both interaction terms and Column (5) additionally includes country-industry-year fixed effects. All specifications include loan and firm controls, rating fixed effects, loan type and purpose fixed effects, lead arranger-year fixed effects, and firm-lead arranger pair fixed effects. In columns (1)-(4), we include industry-year fixed effects while those are replaced by country-industry-year fixed effects in column (5). Standard errors are clustered at the firm and lead arranger levels. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 10: Mechanism: The Role of Predicted Number of New Participants with Little Experience

	Ln(Loan spread)			
	(1)	(2)	(3)	(4)
Local crisis	0.259*** (3.407)	0.170 (0.965)	0.169 (1.027)	
Predicted number of new participants with little experience $\times$ Local crisis	-0.296*** (-3.293)	-0.464*** (-3.256)	-0.382* (-1.928)	-1.514** (-1.987)
Predicted number of new participants with little experience	0.117** (2.335)	0.119* (1.809)	0.052 (0.992)	0.225 (0.575)
Predicted number of all new participants $\times$ Local crisis		0.106 (0.838)	0.080 (0.570)	0.378* (1.900)
Predicted number of all new participants		0.032 (0.204)	-0.015 (-0.071)	-0.029 (-0.100)
High lead arranger country expertise $\times$ Local crisis			-0.091 (-1.197)	0.063 (0.671)
High lead arranger country expertise			0.035 (1.001)	-0.008 (-0.135)
N	7,982	7,982	7,982	7,267
Controls	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓
Loan Type FE	✓	✓	✓	✓
Loan Purpose FE	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	
Country-Industry-Year FE				✓
Lead Arranger-Year FE	✓	✓	✓	✓
Firm-Lead Arranger FE	✓	✓	✓	✓
Adjusted R-squared	0.871	0.871	0.871	0.891

Notes. This table examines whether the predicted number of novice participants (rather than average participation probability) explains the mitigating effect of expert leads. Using first-stage participation regressions, we calculate the predicted number of novice participants ($\widehat{NumNovice}_i$) and the predicted number of all new participants ($\widehat{NumAll}_i$) for each facility. The dependent variable is the natural logarithm of the all-in-drawn spread at loan origination. Column (1) includes predicted novice participant count and its interaction with local crisis. Column (2) adds predicted total participant count. Column (3) adds high lead arranger expertise controls. Column (4) uses country-industry-year fixed effects. All specifications include loan and firm controls, rating fixed effects, loan type and purpose fixed effects, lead arranger-year fixed effects, and firm-lead arranger pair fixed effects. Standard errors are clustered at the firm and lead arranger levels. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Appendix

A Validation Test: Country Expertise and Loan Extension

Appendix Table A.1 validates whether the lender country expertise measure we construct using our data on U.S. publicly listed firms yields results consistent with those reported in Paravisini et al. (2023): specifically, we confirm that firms are, on average, more likely to borrow from lenders that specialize in their main export destinations. To conduct this test, we pair each loan facility from the DealScan loan sample with all active lenders in the loan market, i.e. lenders that participate in any new loan origination in the year prior to the facility start date. As a result, we end up with a loan facility-lender panel with an indicator variable that takes the value of one if the lender is an actual participant of the facility based on DealScan, and zero otherwise. We then regress this indicator on the expertise level of the lender in the borrower’s main export country. This setting allows us to include loan facility fixed effect, which controls for credit demand side as well as loan-specific characteristics that can affect a lender’s propensity to participate in the loan syndicate. In addition, we also include lender $\times$ year fixed effect to control for both time-varying and time-invariant lender-specific characteristics.

Table A.1 presents the results. We categorize lenders’ level of country expertise based on their EXP_b^c in year-country quartiles following Paravisini et al. (2023).²⁹ In the regression, these bank country expertise measures are lagged by one year. Column (1) shows that lenders with the highest level of specialization (top country-year quartile, Q4) in the borrower’s main export country are substantially more likely to participate in the loan facility. While lenders with intermediate-high (Q3) country expertise are also more likely to participate compared to those with intermediate-low (Q2) and low expertise (Q1), the magnitude is significantly smaller than that of the high expertise lenders. We observe a similar pattern for the propensity of a lender participating in the loan syndicate as a lead arranger in Column (4). We then further separate our analysis based on incumbent and outside lenders, based on whether the lender has participated in any loan originated to the borrower of

²⁹We rank lenders for each country-year into quartiles based on the EXP_b^c measure in the full FactSet-DealScan matched sample of firm-country-bank-year observations.

the focal loan facility during the five years prior to its facility start year. Our results suggest that expertise in the borrower's main export country matters for both incumbent and outside lenders. Overall, the results from this examination show that in the United States, a borrower is also more prone to borrowing from lenders that specialize in lending to firms with significant exposure to the same country as its main export country.

Table A.1: Country Expertise and Loan Extension

	D(Loan extension)			D(Loan as lead arranger)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All Lender	Incumbent Lender	Outside Lender	All Lender	Incumbent Lender	Outside Lender
Country expertise:						
Q4	0.053*** (7.228)	0.109*** (5.878)	0.010*** (6.288)	0.036*** (6.352)	0.075*** (4.904)	0.005*** (4.863)
Q3	0.016*** (3.738)	0.045*** (2.701)	0.004*** (2.870)	0.010*** (3.095)	0.028* (1.961)	0.002** (2.425)
Q2	-0.002 (-0.795)	0.017 (1.385)	0.001 (0.549)	-0.004 (-1.531)	0.003 (0.233)	0.000 (0.027)
N	5,178,549	464,621	4,713,453	5,178,549	464,621	4,713,453
Loan Facility FE	✓	✓	✓	✓	✓	✓
Lender-Year FE	✓	✓	✓	✓	✓	✓
Adjusted R-squared	0.233	0.413	0.096	0.172	0.413	0.083

Notes. This table examines whether lenders with higher country expertise are more likely to extend loans to borrowers whose main export destination is that country. We match each loan facility with all active lenders in the market (lenders participating in any new loan in the year prior to facility start). The dependent variable in columns (1)-(3) is an indicator equal to one if the lender participates in the facility. The dependent variable in columns (4)-(6) is an indicator equal to one if the lender participates as a lead arranger. Country expertise quartiles (Q2-Q4) are based on the lender's debt-weighted export specialization measure EXP_b^c in the borrower's main export country, ranked within each country-year. In the regression, these bank country expertise measures are lagged by one year. Q1 (lowest expertise) is the omitted category. Columns (2) and (5) restrict to incumbent lenders (participated in loans to the borrower in prior five years); columns (3) and (6) restrict to outside lenders. All specifications include loan facility fixed effects and lender-year fixed effects. Standard errors are clustered at the firm and lender levels. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

B Leave-One-Borrower-Out Expertise

A lender’s measured expertise EXP_b^c can include its outstanding loans to the focal borrower itself: a lead may appear specialized in a destination partly because it already lends heavily to the very firm whose new facility we analyze. In our sample, roughly 20% of facility-lender pairs have such focal-borrower exposure in the lender’s measured expertise, and removing it changes the measure materially (the correlation between the original and the corrected measure is 0.89). If this contamination drove our results, the paper would be closer to relationship lending than to country specialization.

To assess this, we reconstruct the expertise measure from the raw DealScan and FactSet inputs and recompute it *excluding the focal borrower from both the numerator and the denominator* of equation (2.1), classifying lenders against the same country-year quartile cutoffs. Our reconstruction of the unadjusted measure correlates 0.96 with the original variable; residual differences reflect data vintage. All comparisons below are therefore made *within* the reconstruction—leave-one-out versus unadjusted measures from the identical pipeline—so that vintage differences net out.

Table B.2 reports the results. In Panel A, the composition baseline is unchanged: with the leave-one-out measure for both the lead and the participants, the coefficient on continuous lead expertise is -0.116 ($t = -3.11$) and on the high-expertise indicator -0.007 ($t = -3.12$)—if anything slightly stronger than the same-pipeline unadjusted benchmark (-0.107 and -0.006) and essentially identical to the published estimates. The crisis interaction retains its magnitude (-0.010) with somewhat lower precision ($t = -1.47$), consistent with the country-level inference caveats discussed in Section 5.

For the lender-level participation design, the reconstruction itself is too noisy a vehicle: the participation interaction is small in absolute terms (0.002 on a -0.002 baseline penalty), and reconstruction noise in the expert-lead classification attenuates it regardless of the leave-one-out correction. We therefore apply the correction *surgically*, holding everything else at the original data vintage: for each lead-facility pair, we compute from the reconstruction the fraction of the lead’s measured expertise that survives removing the focal borrower, scale the *original* expertise variable by that fraction, and reclassify leads against the original country-year cutoffs (which we recover exactly—our cutoff-based classification reproduces the original expert-lead indicator with

zero disagreements). The correction demotes 9% of expert-led facilities. Panel B shows the results. The pooled novice interaction is 0.0015 ($t = 1.90$; 0.0017 with lead-lender pair fixed effects, $t = 2.50$), against 0.0017 ($t = 2.03$) under the original classification. Most importantly, the zero-exposure interaction—the paper’s sharpest mechanism result—is 0.0025 ($t = 2.77$) under the leave-one-out classification, against 0.0028 ($t = 2.99$) originally, with positive-exposure novices null in both. We note that the participation design was already largely immune to this concern on the candidate side by construction, since lenders with a prior relationship to the borrower are excluded from the choice set; the correction addresses the lead side.

We conclude that focal-borrower exposure does not drive the specialization–diversification results: measured country expertise reflects destination-country experience beyond the lender’s relationship with the focal firm.

Table B.2: Leave-One-Borrower-Out Expertise

Panel A: Syndicate composition (DV: avg. participant expertise, leave-one-out)					
	Unadjusted (same pipeline)		Leave-one-borrower-out		
	(1)	(2)	(3)	(4)	(5)
Lead arranger country expertise	-0.107** (-2.488)		-0.116*** (-3.107)		
High lead arranger country expertise		-0.006*** (-2.719)		-0.007*** (-3.124)	-0.006*** (-3.170)
High lead expertise $\times$ Local crisis					-0.010 (-1.466)
N	8,721	8,721	8,721	8,721	8,697
Full baseline FE and controls	✓	✓	✓	✓	✓
Adjusted R-squared	0.766	0.765	0.766	0.766	0.766
Panel B: Novice participation at original data vintage (DV: D(Participation))					
	Original	Leave-one-out classification		Original	Leave-one-out
	(1)	(2)	(3)	(4)	(5)
Novice lender	-0.002*** (-4.026)	-0.002*** (-3.946)	-0.001*** (-3.170)		
Novice lender $\times$ High lead expertise	0.002** (2.030)	0.002* (1.904)	0.002** (2.497)		
Zero-exposure lender				-0.001** (-1.989)	-0.001* (-1.743)
Zero-exposure $\times$ High lead expertise				0.003*** (2.994)	0.003*** (2.766)
Low-positive-exposure $\times$ High lead expertise				0.000 (0.129)	0.000 (0.195)
N	2,449,416	2,449,416	2,431,622	2,449,416	2,449,416
Loan Facility FE, Lender-Year FE	✓	✓	✓	✓	✓
Lead arranger-Lender Pair FE			✓		

Notes. This table recomputes the expertise measure excluding the focal borrower from both the numerator and the denominator of equation (2.1). The two panels apply the correction differently. *Panel A uses a full reconstruction:* the measure is rebuilt from the raw DealScan facility data, the outstanding-loan panel, and FactSet Revere geographic revenue exposure (the reconstructed unadjusted measure correlates 0.96 with the original variable), and all columns compare leave-one-out and unadjusted measures from the identical reconstruction so that data-vintage differences net out. *Panel B instead applies a multiplicative leave-one-out correction to the original data vintage:* each lead's original expertise is scaled by the reconstruction-based fraction surviving removal of the focal borrower, then reclassified against the original cutoffs. Panel A re-estimates the composition specification of Table 2, columns (5)-(6), with the average participant expertise computed from leave-one-out member values; lead expertise is the unadjusted reconstruction in columns (1)-(2) and the leave-one-out version in columns (3)-(5); column (5) adds the local crisis interaction. Panel B re-estimates the participation design of Table 5 at the original data vintage: the leave-one-out correction factor from the reconstruction (the fraction of the lead's measured expertise surviving removal of the focal borrower) is applied to the original expertise variable, and leads are reclassified against the original country-year cutoffs, which our cutoff recovery reproduces without error; the correction demotes 9% of expert-led facilities. Column (1) uses the original classification; columns (2)-(3) the leave-one-out classification, with column (3) adding lead arranger-lender pair fixed effects; columns (4)-(5) split novice lenders into zero-exposure and positive-but-bottom-quartile groups under the original and leave-one-out classifications respectively. Standard errors are clustered at the firm and lead arranger levels (Panel A) and the firm and lender levels (Panel B). T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

C A Permutation Benchmark for the Loan-Level Composition Result

A mechanical concern arises in any loan-level composition regression of the form of equation (4.1): because the lead arranger is excluded from the participant average, holding syndicate membership fixed, assigning a higher-expertise member to the lead role automatically lowers the measured average expertise of the remaining participants. If lead roles were systematically assigned to more specialized members, part of the negative association between lead and participant expertise could reflect this exclusion arithmetic rather than differential participation.

We quantify this channel with a permutation benchmark. For each syndicate, we hold the observed membership fixed and reassign the lead role to a uniformly random member, recompute lead expertise and average participant expertise under the placebo assignment, and re-estimate equation (4.1) with all fixed effects re-encoded to the placebo lead’s identity (firm-placebo-lead pair fixed effects and placebo-lead-year fixed effects, along with the unchanged country-industry-year fixed effects and controls). We repeat this 500 times. We also compute a deterministic placebo that assigns the lead role to the highest-expertise member of each syndicate—the sharpest version of the mechanical concern—under the same re-encoded fixed-effect structure.

Three results emerge. First, random role reassignment does generate a negative placebo slope on average (mean -0.062, 5th–95th percentile range [-0.180, 0.048]), confirming that the mechanical exclusion channel is present: with membership fixed, a higher-expertise placebo lead mechanically lowers the mean of the remaining members. Second, the actual estimate (-0.125 when re-estimated on the identical sample) lies at the 82nd percentile of the placebo distribution—twice the mechanical benchmark, with a placebo-adjusted magnitude of -0.063 and a one-sided randomization p -value of 0.18. The observed coefficient is thus more negative than the average mechanical benchmark, although the permutation distribution indicates that exclusion arithmetic explains a meaningful portion of the loan-level association—which is precisely why we do not rest identification on it. Third, the sharpest version of the concern is rejected outright. When the lead role is assigned to the most expert member, the lead’s expertise is by construction the maximum of the syndicate, and therefore an upper bound on every remaining member’s. A syndicate whose placebo lead has low expertise is

one in which no member is highly expert, so the average expertise of the remaining members should be low as well: lead and participant expertise move together rather than in opposition, and the placebo slope is *positive* (0.096, $t = 2.98$). Exclusion arithmetic, pushed to its extreme, thus works against the negative association we estimate rather than producing it. Consistent with this, actual lead arrangers are far from systematically occupying the top of their syndicates' expertise distributions: the lead's expertise sits at the 58th percentile of the within-syndicate distribution on average (percentile ranks computed as $(r - 1)/(n - 1)$ within each facility, so the statistic is not mechanically bounded away from the extremes in small syndicates), and the lead is the maximum-expertise member in 20.6% of facilities, close to the 18.6% expected under random role assignment.

We therefore read the loan-level magnitudes in Tables 2–4 as descriptive of the equilibrium matching between lead specialization and participant composition, and rest the identification of differential participation on the lender-level design of Section 4.3, which is immune to the exclusion arithmetic by construction: it compares participation decisions across candidate lenders facing the same facility, rather than measuring the composition of the residual syndicate.

D Additional Figures and Tables

Table D.3: Post-Participation Expertise of Novice Entrants: Event-Study Estimates

	EXP_b^c		$D(EXP_b^c > 0)$	
	(1)	(2)	(3)	(4)
High lead expertise $\times (t - 3)$	0.008* (1.813)	0.007 (1.514)	0.008 (0.195)	0.003 (0.064)
High lead expertise $\times (t - 2)$	0.003 (0.859)	0.005 (1.265)	0.011 (0.371)	0.038 (1.082)
High lead expertise $\times (t)$	0.009 (1.628)	0.010* (1.835)	0.005 (0.178)	0.017 (0.478)
High lead expertise $\times (t + 1)$	0.012* (1.940)	0.015** (2.288)	0.023 (0.725)	0.039 (0.982)
High lead expertise $\times (t + 2)$	0.007 (1.279)	0.009 (1.535)	-0.035 (-1.117)	-0.019 (-0.487)
High lead expertise $\times (t + 3)$	0.013* (1.891)	0.016** (2.358)	-0.018 (-0.522)	0.010 (0.227)
N	5,138	5,052	5,138	5,052
Event FE	✓	✓	✓	✓
Country-Year FE		✓		✓
Adjusted R-squared	0.409	0.424	0.648	0.641

Notes. This table reports event-study estimates of novice entrants' expertise around their first participation in a loan exposed to a given export market, comparing entrants under high-expertise (top-quartile) lead arrangers to entrants under non-expert leads. Events are the first facility participation by a novice (bottom-quartile expertise) lender in a loan whose borrower's main export country is c (956 events, of which 274 are expert-led). The dependent variable is the entrant's expertise EXP_b^c in the destination country (columns 1-2) or an indicator for positive expertise (columns 3-4), measured over expertise years $t - 3$ to $t + 3$ relative to the origination year t ; the omitted baseline is the year preceding origination ($t - 1$). Reported coefficients are interactions between an indicator for an expert-led event and event-time indicators; event-time main effects are included but unreported. All specifications include event fixed effects; columns (2) and (4) add country-calendar-year fixed effects. The joint test of the two pre-event interactions in column (2) has p -value 0.28. Standard errors are clustered at the lender level. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table D.4: Stable-Destination Borrower Sample

	Average loan participant country expertise	
	(1)	(2)
Lead arranger country expertise	-0.218*** (-5.458)	
High lead arranger country expertise		-0.019*** (-6.169)
N	2,960	2,960
Loan and Firm Controls	✓	✓
Rating, Loan Type, Loan Purpose FE	✓	✓
Country-Industry-Year FE	✓	✓
Lead Arranger-Year FE	✓	✓
Firm-Lead Arranger FE	✓	✓
Adjusted R-squared	0.642	0.644

Notes. This table re-estimates the baseline composition specification of Table 2, columns (5)-(6), on the subsample of borrowers whose main export destination never changes over the sample period, so that all identifying variation within a firm-lead arranger pair comes from the evolution of lender expertise for a fixed destination rather than from destination switching. Standard errors are clustered at the firm and lead arranger levels. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table D.5: Post-Entry Participations Outside the Certifying Lead's Network

	# new participations		Any participation	Leads any facility
	(1)	(2)	(3)	(4)
High lead arranger country expertise	-2.381** (-2.455)	-4.822*** (-2.972)	-0.004 (-0.091)	-0.009 (-0.262)
Pre-entry participation count	1.061*** (11.946)	1.092*** (12.452)	0.006*** (4.242)	0.008*** (6.331)
N	943	827	827	827
Country FE, Entry-Year FE	✓			
Country × Entry-Year FE		✓	✓	✓
Adjusted R-squared	0.526	0.553	0.328	0.082

Notes. This table asks whether novice entrants expand into the destination market *independently* of the arrangement through which they entered. For each first novice participation event (as in Figure 2), the dependent variable counts the entrant's participations in facilities exposed to the same destination country during the three years after entry, *excluding* the entry borrower and all facilities arranged by the entry lead (columns 1-2), an indicator for any such participation (column 3), and an indicator for the entrant leading any such facility (column 4). Expert-led entrants expand significantly *less* outside the original arranger's network on the count margin, with no difference at the any-participation margin; combined with the expertise growth in Figure 2, this indicates that post-entry expansion operates within the certifying lead's network rather than through autonomous market entry. Standard errors are clustered at the lender level. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table D.6: A Predetermined Network Measure of Prospective Low-Exposure Participation

	Ln(Loan spread)		
	(1)	(2)	(3)
Local crisis	0.034** (2.197)	0.049** (2.339)	
NetLow $\times$ Local crisis	0.153 (1.317)	0.095 (0.633)	-0.098 (-0.773)
NetLow	0.309 (1.172)	0.325 (1.271)	0.487 (0.333)
High lead arranger country expertise $\times$ Local crisis		-0.129 (-1.656)	
High lead arranger country expertise		0.036** (2.520)	
N	7,955	7,955	7,101
Industry-Year FE	✓	✓	
Country-Industry-Year FE			✓
Lead Arranger-Year FE	✓	✓	✓
Firm-Lead Arranger FE	✓	✓	✓
Adjusted R-squared	0.868	0.869	0.890

Notes. This table reports the predetermined alternative to the fitted-probability participation measure discussed in Section 5.3.3. NetLow is the share of the lead arranger's syndication partners over the prior three years (distinct lenders appearing in facilities it arranged) whose expertise in the borrower's main export country, measured in the year before origination, is in the bottom quartile or zero; the measure is centered at its mean. The interaction with the local crisis indicator is statistically indistinguishable from zero in all specifications, which is why we treat the participant-composition pricing evidence as suggestive rather than identified. All specifications include loan and firm controls, rating fixed effects, and loan type and purpose fixed effects. Standard errors are clustered at the firm and lead arranger levels. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table D.7: Crisis-Period Intensification among Borrowers with Material Export Exposure

	Average loan participant country expertise	
	Full sample (1)	Rev. share > 10% (2)
High lead arranger country expertise	-0.007*** (-4.717)	-0.007* (-1.710)
High lead arranger country expertise $\times$ Local crisis	-0.010** (-2.389)	-0.027*** (-4.342)
N	8,697	3,457
Controls	✓	✓
Rating FE	✓	✓
Loan Type FE	✓	✓
Loan Purpose FE	✓	✓
Country-Industry-Year FE	✓	✓
Lead Arranger-Year FE	✓	✓
Firm-Lead Arranger FE	✓	✓
Adjusted R-squared	0.771	0.759

Notes. This table re-estimates the crisis-interaction specification of Table 8 on the subsample of borrowers deriving more than 10% of revenue from their main export market, the materiality threshold used in Table 4. Column (1) reproduces column (2) of Table 8 for comparison; column (2) restricts the sample to materially exposed borrowers. The interaction in column (2) is also robust to inference that respects the country-level variation in the crisis indicator: a wild-cluster bootstrap by destination country yields $p = 0.03$. All specifications include loan and firm controls, rating fixed effects, loan type and purpose fixed effects, country-industry-year fixed effects, lead arranger-year fixed effects, and firm-lead arranger pair fixed effects. Standard errors are clustered at the firm and lead arranger levels. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table D.8: Crisis-Pricing Inference: Alternative Clustering and Leave-One-Country-Out

Panel A: Alternative inference for the interaction $HighLeadExp \times LocalCrisis$			
	Coefficient	t -statistic	Wild bootstrap p
Clustered by firm and lead arranger (baseline)	-0.149	-2.23	
Clustered by destination country	-0.149	-2.20	<0.01
Clustered by firm, lead arranger, and country	-0.149	-2.18	
Panel B: Leave-one-country-out (ten largest destination markets)			
Excluded market	Coefficient	t -statistic	
Australia	-0.151	-2.33	
Brazil	-0.144	-2.21	
Canada	-0.248	-2.26	
France	-0.140	-2.09	
Germany	-0.143	-2.19	
Italy	-0.132	-2.31	
Japan	-0.222	-2.09	
Mainland China	-0.121	-1.49	
Mexico	-0.161	-2.12	
United Kingdom	-0.122	-1.58	

Notes. Panel A re-estimates the pricing specification of Table 9, column (2), under alternative treatments of the country-level variation in the crisis indicator. The wild-cluster bootstrap (999 replications, Rademacher weights) is computed on the Frisch-Waugh residualized regression clustered by destination country; the bootstrap p -value for the standalone crisis effect is 0.02. Panel B re-estimates the same specification excluding, one at a time, each of the ten largest destination markets. All point estimates remain negative; precision falls below conventional levels only when excluding mainland China or the United Kingdom, the two largest suppliers of crisis-period observations (Appendix Table D.10). T -statistics use the baseline firm and lead arranger clustering.

Table D.9: Restricted Choice Sets and the Zero-Exposure Margin

	D(Participation)		
	Restricted choice set (1)	Restricted choice set (2)	Full choice set (3)
Novice lender	-0.003*** (-3.538)		
Novice lender×High lead arranger country expertise	0.002 (1.494)		
Zero-exposure lender		-0.002 (-1.235)	-0.001** (-1.989)
Zero-exposure lender×High lead expertise		0.004*** (2.870)	0.003*** (2.994)
Low-positive-exposure lender		-0.003*** (-2.992)	-0.002*** (-3.204)
Low-positive-exposure lender×High lead expertise		0.000 (0.039)	0.000 (0.129)
N	1,111,776	1,111,776	2,449,416
Loan Facility FE	✓	✓	✓
Lender-Year FE	✓	✓	✓
Adjusted R-squared	0.091	0.091	0.074

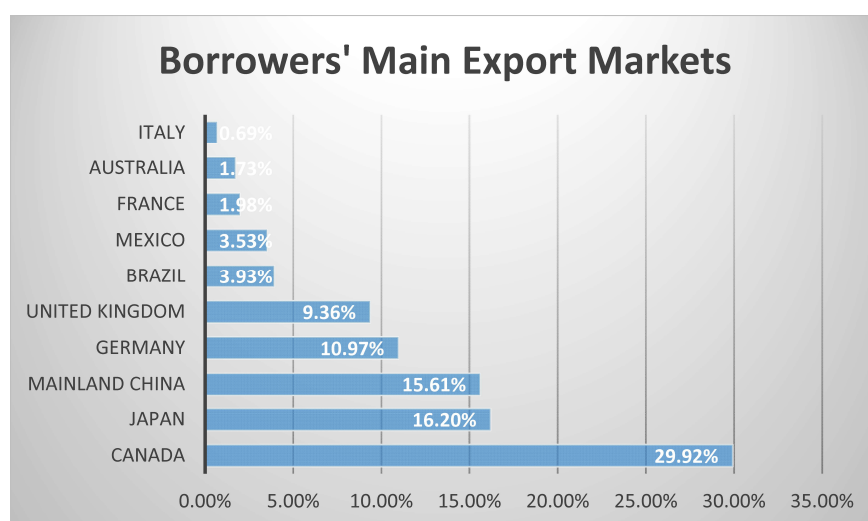
Notes. This table refines the loan-issuance participation design of Table 5. Columns (1)-(2) restrict the candidate lender pool to lenders that participated, in the year prior to the facility start, in at least one facility of the same loan-type group (credit line versus term loan) and the same one-digit borrower industry. Column (3) uses the full candidate pool. Novice lender is an indicator for bottom-quartile expertise in the borrower's main export country; columns (2)-(3) split novices into lenders with strictly zero prior exposure and lenders with positive but bottom-quartile exposure. The dependent variable equals one if the lender participates in the facility. All specifications include loan facility fixed effects and lender-year fixed effects; standard errors are clustered at the firm and lender levels. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table D.10: Local Crisis Episodes Supplying Identification

Main export market	Crisis years	Facilities originated during crisis years
Mainland China	2012–2013, 2015–2019	1,186
United Kingdom	2016–2017, 2019	228
Brazil	2015–2017	91
Japan	2011–2012	72
Mexico	2017–2018	43
Russian Federation	2011–2012, 2014–2015	23
Italy	2011–2012	5
Ireland	2011–2012	4
Spain	2011–2012	3
Egypt	2011–2012	2
Nigeria	2004	1
Thailand	2015	1

Notes. This table lists the local crisis episodes, as classified by [Hassan et al. \(2024\)](#) and mapped into our annual crisis indicator (year t or $t - 1$ in crisis), that supply identification in the crisis analyses. Facility counts are distinct loan facilities in the spread sample whose borrower’s main export market is the listed country in a crisis year. Prominent episodes include the 2012 “hard landing” concerns and 2015–2016 equity market turmoil in China, the 2016 Brexit referendum in the United Kingdom, the 2015–2016 corruption scandal in Brazil, the 2011 Fukushima disaster in Japan, and the 2011–2012 European sovereign debt crisis (Italy, Ireland, Spain).

Figure D.1: Distribution of Borrowers' Main Export Markets



Notes. This figure shows the geographic distribution of borrowers' main export destinations in our loan sample. The main export country is defined as the country (excluding the United States) where the borrower has the largest revenue exposure share based on FactSet Revere data. The sample covers syndicated loan facilities to U.S. publicly listed firms from 2004 to 2019.

Table D.11: Controlling for Lead Arranger Industry Expertise

	Average loan participant country expertise	
	(1)	(2)
Lead arranger country expertise	-0.155*** (-3.275)	
High lead arranger country expertise		-0.009*** (-5.212)
N	7,976	7,976
Loan controls	✓	✓
Firm controls	✓	✓
Rating FE	✓	✓
Loan Type FE	✓	✓
Loan Purpose FE	✓	✓
Country-Industry-Year FE	✓	✓
Lead Arranger-Industry-Year FE	✓	✓
Firm-Lead Arranger FE	✓	✓
Adjusted R-squared	0.733	0.733

Notes. This table replicates the baseline analysis while controlling for lead arranger industry-specific lending practices. The dependent variable is the average country expertise of participant lenders in the borrower's main export country. The key difference from Table 2 is the inclusion of lead arranger-industry-year fixed effects, which absorb all variation in a lead arranger's lending behavior to a specific industry in a given year. This ensures our country expertise effects are not driven by industry specialization. All other controls and fixed effects are as described in Table 2. Standard errors are clustered at the firm and lead arranger levels. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table D.12: Excluding NAFTA Export Destinations

	Average loan participant country expertise	
	(1)	(2)
Lead arranger country expertise	-0.145*** (-2.663)	
High lead arranger country expertise		-0.012*** (-3.571)
N	5,636	5,636
Loan controls	✓	✓
Firm controls	✓	✓
Rating FE	✓	✓
Loan Type FE	✓	✓
Loan Purpose FE	✓	✓
Country-Industry-Year FE	✓	✓
Lead Arranger-Year FE	✓	✓
Firm-Lead Arranger FE	✓	✓
Adjusted R-squared	0.764	0.764

Notes. This table replicates the baseline analysis excluding loans to borrowers whose main export destination is Canada or Mexico. The dependent variable and all controls and fixed effects are as described in Table 2. This restriction ensures our results are not driven by exports to geographically proximate NAFTA partners, which may be perceived as less risky or more familiar to U.S. lenders. Standard errors are clustered at the firm and lead arranger levels. T-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.